REPUBLIC OF TURKİYE

ALTINBAŞ UNIVERSITY

Institute of Graduate Studies

Information Technology

TUMOR DETECTION IN SPINAL CORDS USING SIGMOID BASED CNN ALGORITHM

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Master's Thesis

Supervisor

Prof. Dr. Osman Nuri UÇAN

Istanbul, 2023

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2023

The thesis titled TUMOR DETECTION IN SPINAL CORDS USING SIGMOID BASED CNN ALGORITHM prepared by SHERHAN AIAD ALSUNOUS ABOKHNANA and submitted on 10/04/2023 has been accepted unanimously for the degree of Master of Science in Information Technology.

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Sherhan Aiad Alsunous ABOKHNANA

Signature

DEDICATION

I thank God Almighty for helping me and granting me success in completing this thesis.

This thesis is wholeheartedly devoted to the memory of my mother and father. It is impossible for me to put into words how much it means to me. There is absolutely nothing I can do to make up for what you have done to me. I shall keep doing everything in my power to live up to the standards you have set.

In conclusion, I would want to say thank you to my family. They helped me a lot and encouraged me to complete this project.

PREFACE

First of all, I thank Allah Almighty for helping me complete this thesis.

I am pleased to extend my thanks, appreciation and gratitude to my honorable supervisor, Prof. Dr. Osman Nuri UÇAN, who I was pleased to his supervision on this research for his efforts to create a scientific environment and to overcome all the difficulties that I faced throughout the research period. I extend my thanks to the Altınbaş University, Department of Computer Engineering / Information Technologies, for supporting me in completing this work. I special thanks to my mother, who supported me with her prayers, and my wife, who was my support at this stage and did not leave me alone at all times with such circumstances. I appreciate my friends and everyone who encouraged me and contributed to the success of this study.

Finally, I would like to thank everyone who helped me with their advice and efforts.

ABSTRACT

TUMOR DETECTION IN SPINAL CORDS USING SIGMOID BASED CNN ALGORITHM

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Date: April / 2023

Pages: 54

Abnormal growths called spinal tumours can develop inside the spine or on the outside of the spinal cord. Depending on where they are located and how big they are, these tumors which can either benormal or malignant (cancerous) can produce a range of symptoms. Improving patient outcomes and lowering morbidity and mortality depend on early diagnosis and treatment. The purpose of this study is to improve the accuracy and efficacy of spinal tumour identification. We'll talk about how to automatically recognise the spinal cord and provide a reliable technique for highlighting and recognising the oesophagus during MRI scan preparation.

Keywords: Spinaltumor, CNN, CT, Classification, Machine Learning.

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ABBREVIATIONS

AI	:	Artificial Intelligence
ML	:	Machine Learning
CNN	:	Convolutional Neural Network
CT	:	Computerised Tomography

1. INTRODUCTION

1.1 INTRODUCTION

A spinal tumor is a mass of abnormal cells that grows within the spine or on the surface the spinal column [29]. These tumours can develop at any level of the spine, from the cervical (upper back) region to the lower back and they can be harmless or cancer [30]. Numerous things, such as genetics, exposure to radiation or hazardous substances, and diseases, can result in them [31]. Depending on where they are and how big they are, spinal tumours can present with a number of symptoms [32]. Imaging procedures like CT scans and MRIs can help diagnose spinal tumours. Depending on the precise extent and type of the tumour, effective treatments could include operation, radiotherapy, and chemotherapy [1]. Spinal tumors are abnormal growths that can occur within the spine or on the surface of the spinal cord [33]. These tumors can be benign (non-cancerous) or malignant (cancerous) and can cause a variety of symptoms depending on their location and size [34]. Early detection and treatment of spinal tumors is important for improving patient outcomes and reducing morbidity and mortality [35]. Artificial intelligence (AI) algorithms known as convolutional neural networks are extremely effective in classifying images [36]. In this thesis, we suggest that medical imaging data be used to train CNNs to build a model for identifying spinal cancers. In order to enable early recognition and treatment of these tumours, the aim of this research is to increase the reliability and effectiveness of spinal tumour detection. To achieve this goal, we will obtain and annotate a dataset of medical imaging studies that include both normal and abnormal spinal scans. We will then train and evaluate a CNN model on this dataset to predict whether a given scan contains a spinal tumor. We will also explore various techniques for improving the performance of the model, such as data augmentation and transfer learning. Overall, this project has the potential to significantly impact the field of spinal tumor detection and contribute to the overall improvement of patient care.

1.2 MOTIVATION

Early detection: Based on where they are and how big they are, spinal tumours can produce a range of symptoms, and early detection is important for improving patient outcomes and reducing morbidity and mortality. A CNN model for detecting spinal tumors could help to facilitate earlier diagnosis and treatment of these tumors.

Improved accuracy: Traditional methods for detecting spinal tumors, such as manual review of medical imaging studies by radiologists, can be time-consuming and prone to error. A CNN model could potentially improve the accuracy of spinal tumor detection by automating the process and reducing the need for manual review.

Increased efficiency: A CNN model for spinal tumor detection not only enhances accuracy but also hastens the diagnostic process by enabling quick review of numerous imaging studies. This leads to shorter wait times for patients and prompt treatment.

Enhanced patient care: Ultimately, the development of a CNN model for detecting spinal tumors could contribute to the overall improvement of patient care by facilitating earlier diagnosis and treatment of these tumors. This could help to shrink the negative effectiveness of spinal tumors on the patient's life and improve their overall quality of life.

1.3 PROBLEM STATEMENT

Spinal tumors are abnormal growths that can occur within the spine or on the surface of spinal cord [1]. Depending on where they are located and how big they are, these tumours can be benign or malignant and present with a range of symptoms. For patients to have better results and experience a decrease in morbidity and mortality, diagnosis and treatment of spinal tumours are crucial. However, traditional methods for detecting spinal tumors, such as manual review of medical imaging studies by radiologists, can be time-consuming and prone to error [37].Radiotherapy is a treatment method that inhibits the proliferation of cancer cells or employs high-energy radiation to accomplish this [38]. While it has many advantages, the use of radiotherapy requires strict adherence to treatment protocols, specialized software for planning, and a thorough analysis of the risks for each patient [39]. However, mistakes can appear, leading to irreparable injury to the patient. Both immediate and long-term negative effects might result from radiotherapy. To better understand the effects and hazards of radiation, researchers have performed studies including patients who were followed up over an extended period of time [40]. One prevalent side effect of radiotherapy, for instance, is severe late-term intestinal damage, according to a study of 515 women with cervical cancer. Researchers have also created new methods and carried out more study to address the potential side effects of radiation. These contemporary methods may increase cure rates and lessen side effects. In order to maximise the overall outcomes,

all patients with newly diagnosed conditions undergo multidisciplinary evaluations where the relative merits of surgery, radiation, and chemotherapeutic are each taken into account.

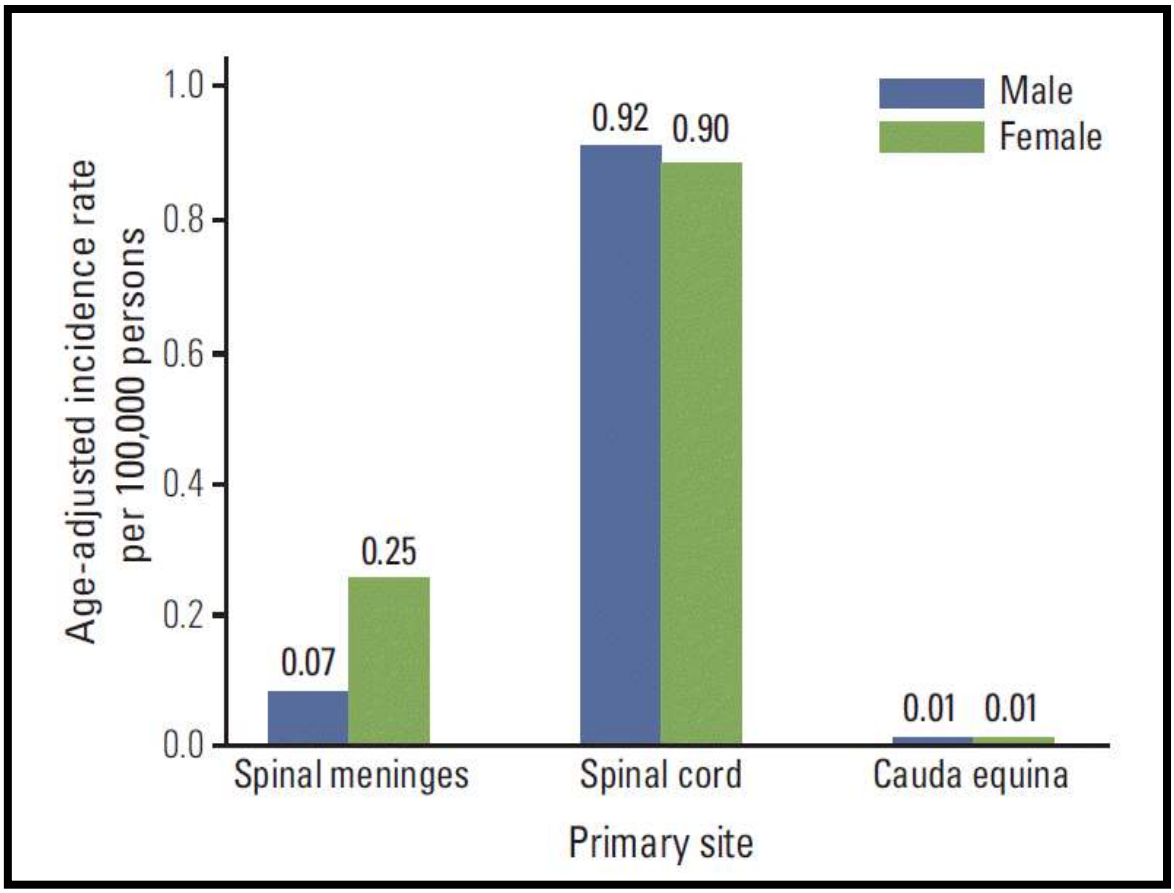

Figure 1.1: Spinal Tumor [41].

1.4 RESEARCH HYPOTHESES

The following hypotheses are being considered in this study based on the research questions:

reducing the region of interest in MRI scans can reduce computational load and improve the performance of the final segmentation of the spinal cord and esophagusTraditional image processing techniques are sufficient for initial segmentation of the spinal cordStandardizing images and using this standardized information in the form of a probabilistic atlas is helpful for initial segmentation of the esophagusImage filtering techniques can be used to enhance MRI scans and improve the visibility of the esophagus

Supervised machine learning techniques are effective for segmenting the spinal cord and esophagusImage processing techniques can improve the results obtained from machine

learning modelsThese hypotheses will be tested and confirmed through the techniques and methods used and the results achieved in the proposed methods.

1.5 RESEARCH OBJECTIVES

i. The key objective of our thesis is to create computational methods depending on image processing and pattern recognition techniques for automatically segmenting the spinal cord and esophagus in intending computed tomography scans for radiotherapy. To achieve this goal, the following specific objectives will be pursued:

ii. Increasing knowledge about CT in radiotherapy treatment

iii. Improving the template matching technique for use in MRI scans, making it adaptable to different slices

iv. Examining various superpixel techniques

v. Identifying effective filters to enhance the visibility of the esophagus in MRI scans

vi. Studying convolutional neural networks (CNNs) and their potential application in spinal cord and esophagus segmentation

vii. Validating the proposed methods using commonly used metrics in medical imaging and comparing the proposed methods to established methods in the literature

The proposed methods will contribute to the field in several ways, including:

i. Improving the template matching technique for use in MRI scans

ii. Applying iterative clustering at the beginning in medical images and achieving hopeful outcomes

iii. Outlining an architecture for CNN that can classify superpixels as part of the spinal cord

iv. Enhancing the visibility of the esophagus in MRI scans using image processing filters

v. Proposing a fully convolutional network (FCN) architecture that can effectively segment the esophagus

vi. Developing two robust methods for automatically. MRI scan preparation to correctly identify the spinal cord.

vii. Proposing a robust method for automatically highlighting and detecting the esophagus in planning MRI scans

viii. Overall, these efficient methods can be used in the planning of MRI-based radiotherapy systems to save time and assist specialists in the researchfordetecting the illness and esophagus.

1.6 THESES ORGANIZATION

The chapters of our research is as follows:

i. In Chapter 2, the previous related studies, will be presented and how our method fills gaps in existing works.

ii. Chapter 3 will present fundamental concepts relevant to the understanding of the proposed methods.

iii. In Chapter 4, the methods used for the purpose of categorizing the spinal cord in CT images and the results obtained will be presented.

iv. In Chapter 5, the method used to segment the esophagus in CT images and the results obtained will be presented.

v. Finally, in Chapter 6 the conclusions of the work will be presented, where an evaluation of the proposed methods and future plans for their improvement are made.

2. LITERATURE REVIEW

2.1 INTRODUCTION

Abnormal growths called spinal tumours can develop inside the spine or on the outside of the spinal cord [42]. Depending on where they are located and how big they are, these tumours may be benign or malicious present with a range of symptoms [43]. For patients to have better results and experience a decrease in morbidity and mortality, detection and treatment of spinal tumours are crucial. Although time-consuming and prone to error, conventional methods in the convolutional neural networks (CNN) for finding spinal tumours [44], such as manual evaluation of medical imaging data by radiologists Researchers have investigated the use of computational techniques, such as machine learning (ML) algorithms [45], for the detection of spinal cancers in order to overcome these difficulties. For image classification and segmentation tasks, CNNs, a form of ML method, have been employed extensively [46]. In this literature review, we will examine the use of CNNs for detecting spinal tumors from medical imaging data. We will review the state of the approaches and methodolgies, including the performance of different CNN architectures and the impact of various factors on the accuracy of spinal tumor detection using CNNs. We will also discuss the potential benefits and limitations of using CNNs for spinal tumor detection, as well as directions for future research.

2.2 PREVIOUS STUDIES

We shall cover similar studies that have been conducted in this subject under the related work because our study topic is still in its early phases. By analysing how well the Massachusetts Spine Tumor Functional Index (MSTFI) predicted severe complications, in-hospital mortality, and length of hospital stay (LOS) for patients with metastatic spinal tumours who needed surgery at the Massachusetts General Hospital between 2010 and 2019, The authors of [2] aimed to improve accuracy through their study. They used 479 older adults as a validation cohort for the MSTFI and evaluated the 9 parameters of the MSTFI using 3 machine learning methods (lasso regularization LR, RF, and XGBoost). To assess the models' performance, they used AUROCs, calibration, and confusion matrix metrics. The results showed that the MSTFI had limited ability to predict complications (56%) and in-hospital mortality (69%). Although the MSTFI was originally developed with a logistic

regression model, the machine learning approaches improved the prediction of surgical problems.

The most effective predictors of surgical patients according to the random forest model were chronic lung disease, coagulopathy, anaemia, and malnutrition the result for positive prediction achieved 53% and the value of predicting the negative was 77%. In this study [3], the authors created a system for classifying, segmenting, and visualising large-scale tissue histopathology documents using deep convolutional neural networks (CNNs). The framework entails applying characteristics learned by CNNs trained on a sizable library of natural photos to histopathology images. By observing how individual neurons responded in the last layer, the researchers also investigated the properties of CNN features and discovered that several of these features gave biological insights that were corroborated by pathologists. The suggested framework performed at the cutting edge when evaluated on datasets of brain tumours and histopathological images of bowel cancer. The efficacy of image features recovered from various lengths of image transform chains for picture classification was examined in this study [4].

The raw images, image transforms, and compound image transforms of second, third, and fourth order were used to extract the features. The Fourier, Chebyshev, and Wavelet (symlet 5) transforms were employed in the investigation. The findings demonstrated that, in some circumstances, image features extracted from the first and second orders of compound image transforms can be more informative than those retrieved from raw pixels and can greatly increase the classification accuracy. However, utilising chains of transforms longer than 2 did not boost the study's image datasets accuracy of classification.

This study [5] explored the classification of pneumonia using chest X-ray images and a CNN-based approach. Three methods were evaluated: a capsule network trained from scratch, transfer learning on two CNN models (VGG16 and Inception), and a linear SVM classifier with local rotation and orientation-free data. All three strategies utilized data augmentation in data preparation. The results showed that all three algorithms performed better overall when transfer learning was used. On a smaller dataset, a SVM with oriented fast and rotated binary (ORB) robust independent elementary features and a capsule network were less effective than transfer learning. Transfer learning performance can be improved

by fine-tuning specific features on the target dataset, and choosing the appropriate network complexity for the dataset size is crucial.

The study in [6], addressed the auto-multiclass of segmenting the spinal cord, this study designed a model for the segmentation of spinal cord tumours. The data from 343 patients was gathered through MRI scans using T1-weighted and T2-weighted contrast agents that covered the cervical, chest wall, and/or lumbar areas.Astrocytomas, ependymomas, and hemangioblastomasthe three most prevalent subtypes of intramedullary spinal cord tumors—are included in the dataset. The suggested method divides tumours into two stages: detect and label. It uses a multilevel inverter structure and U-Net-based algorithms.The spinal cord is initially located by the model, which then produces bounding box coordinates. According to this output, the photos are trimmed, which results in a narrower field of view and lessens the disparity in class. The tumour was segmented, resulting in a 76.7% segmentation of the tumour, cavity, and edema as a single class.

Various methods for feature extraction and classification using CNNs have been proposed, and it has been demonstrated that these methods can achieve high performance in various medical imaging tasks. However, there are also challenges to be addressed in the development and implementation of CNNs for spinal tumor detection, such as the limited possibility of marked healthcare image datasets and the need for careful design and optimization of the CNN architecture to ensure good generalization to new data.

2.3 SPINAL TUMOR

Spinal tumors are abnormal growths that can occur within the spine or on the surface of the spinal cord [1]. Some common symptoms of spinal tumors include back pain, changes in the bladder or bowel function, arm or leg numb or strength, and trouble balancing or walking [47,48]. Since they frequently don't present with symptoms until they have gotten to be quite large, spinal tumours can be challenging to find. Therefore, it is important to get regular check-ups and medical imaging studies if you have risk factors for spinal tumors, such as a family history of cancer or a history of radiation exposure [49]. Early detection and treatment of spinal tumors can improve patient outcomes and reduce morbidity and mortality. Treatment options for spinal tumors may include surgery, radiotherapy, or chemotherapy, depending on the type and stage of the tumor. Depending on where they originate, spinal

tumours can be categorised as primary or metastatic. Primary spinal tumours, which make up a small portion of all spinal tumours and are generally uncommon, begin in the spine. Metastatic spinal tumours, on the other hand, represent tumors that have spread from other parts of the body to the spine. These tumours are more prevalent and usually cancerous. In the course of their illness, between 30 to 70 percent of cancer patients may develop metastatic spine cancer, with lungs, prostatic, and breast cancers among the most common to do so [7]. Spinal tumors can be classified as primary or metastatic based on their origin. An abnormal growth or mass that can develop inside the spine or on the outside of the spinal cord is referred to as a "spinal tumour." Depending on where they are located and how big they are, these tumours can be benign (non-cancerous) or malignant (cancerous) and present with a range of symptoms. Back pain, numbness or weakening in the arms or legs, trouble walking or balancing, and changes in bowel or bladder function are some of the typical symptoms of spinal tumours. Depending on where they originate, spinal tumours can be categorised as primary or metastatic. Primary spinal tumours, which make up a small portion of all spinal tumours and are generally uncommon, begin in the spine. These tumors are more common and are typically malignant.The type and stage of the tumour, as well as the patient's general condition, all influence the available treatments for spinal tumours. Surgery to remove the tumour, radiotherapy to treat cancer, and chemo to limit the spread of cancer cells are common treatment choices. A combination of these therapies may be applied in some situations. In order to choose the best course of therapy for your particular needs, it is crucial to collaborate with a healthcare team.

2.4 TYPES OF SPINAL TUMOR

There are several types of spinal tumors, which can be classified based on their location within the spine, their tissue type [8], and whether they are benign (non-cancerous) or malignant (cancerous). Here are a few examples of different types of spinal tumors:

a. Meningiomas [50]: The most typical kind of recurrent spinal tumours are meningiomas. The meninges, the membranes that cover the brain and spinal cord, are the source of these benign tumours. Meningiomas can develop anywhere along the spine, although the thoracic and lumbar regions are where they most frequently occur.

b. Schwannomas [51]: Schwannomas are normaltumors that appear from the Schwann cells, which are responsible for producing the protective myelin sheath around nerves. Schwannomas can occur anywhere in the spine but are most common in the neck and upper back.

c. Osteoblastomas [52]: Osteoblastomas are emerging pituitary tumors. it occur from the bone cells (osteoblasts) and tend to occur in the spine of young adults.

d. Chordomas [53]: The remnants of the notochord, a structure that develops during foetal development, give rise to these uncommon, slowly developing tumours. Chordomas tend to occur in the sacrum (lower back) and can be difficult to treat due to their location.

e. Sarcomas [54]: Sarcomas are cancerous tumors that appear from connective tissue, such as bone, muscle, or fat. They can occur anywhere in the spine and can be aggressive and difficult to treat.

f. Leukemias [55]: Leukemias are cancerous tumors that arise from blood-forming cells in the body. Ependymomas: These are tumors that arise from the ependymal cells, which line the ventricles (cavities) in the brain and the central canal of the spinal cord. Ependymomas can occur anywhere in the spine and can be benign or malignant.

g. Astrocytomas [56]: These are tumors that arise from astrocytes, which are a type of glial cell in the brain and spinal cord. Astrocytomas can occur anywhere in the spine and can be benign or malignant.

h. Glioblastomas [57]: These are the most aggressive and malignant type of glioma, which is a type of brain or spinal cord tumor that arises from glial cells. Glioblastomas are typically located in the brain, but they can also occur in the spine.

i. Hemangioblastomas[58]: These blood vessel-derived benign tumours generally develop in the brain and spine.They tend to occur in people with von Hippel-Lindau disease, which is a rare genetic disorder.

j. Vertebral hemangiomas [59]: These are benign tumors that arise from blood vessels in the vertebrae (bones of the spine). They are usually asymptomatic and do not require treatment unless they are causing symptoms or compressing the spinal cord.

k. Lymphoma [60]: This is a type of cancer that arises from immune cells called lymphocytes. Lymphomas can occur anywhere in the body, including the spine, and can be benign or malignant.

l. Ewing sarcoma [61]: This is a rare, aggressive type of cancer that arises from bone or soft tissue and it's possible to appear anywhere in the body, within the spine too.

2.5 SPINAL TUMOR CLASSIFICATION

Spinal tumors can be classified in a number of ways [10], including by their location in the spine, their tissue type, and their behavior (benign or malignant). Here are some examples of how spinal tumors can be classified [9]:

Location: Spinal tumors can occur anywhere in the spine, including the cervical spine (neck), thoracic spine (upper back), lumbar spine (lower back), and sacral spine (pelvic area).

Tissue type: Spinal tumors can be classified based on the type of tissue they originate from. For example, some common tissue types for spinal tumors include bone, nerve, muscle, blood vessels, and connective tissue.

Behavior: Spinal tumors are divided into two categories based on their nature: benign and malignant. Benign tumors are non-cancerous and grow at a slow pace. They do not spread and are typically easier to treat. On the other hand, malignant tumors are cancerous, grow rapidly, and can spread to other parts of the body, making them more challenging to treat.

2.6 CAUSES

The main reason of a spinal tumor is often unknown [11]. However, some factors that may boost the risk of developing a spinal tumor include:

a. Age: Spinal tumors are more common in older people, especially those over the age of 50.

b. Family history: Some people may have a higher risk of developing a spinal tumor if they have a family history of the condition.

c. Genetic traits: Neurofibromatosis and von Hippel-Lindau disease are two genetic illnesses that raise the likelihood of having a spinal tumour. Previous radiation therapy: People who have received radiation therapy for cancer in the past may have an increased risk of developing a spinal tumor later in life.

d. Exposure to certain chemical: such like exposure to benzene, may raise the risk of developing a spinal tumour.

2.7 SYMPTOMS

The symptoms and warning signs of a spinal tumour might change based on the tumor's size, nature, location, and growing pace [12]. The following are some typical signs of a spinal tumour:

i. Back pain: This is often the most common symptom of a spinal tumor. The pain may be constant or intermittent and may be worse at night or when lying down.

ii. Numbness or weakness: A spinal tumor can press on nerves or the spinal cord, causing numbness or weakness in the arms, legs, or other parts of the body.

iii. Difficulty walking: A spinal tumor can cause problems with balance and coordination, making it difficult to walk or stand.

iv. Loss of bladder or bowel control: A spinal tumor that presses on the spinal cord can cause problems with bladder or bowel control.

v. Unexpected weight loss: Some people with a spinal tumor may experience unexpected weight loss.

vi. Changes in posture: A spinal tumor may cause changes in posture, such as a hunched back or a tilt to one side.

It is important to note that not all spinal tumors cause symptoms, and some people with a spinal tumor may not experience any symptoms at all.

2.8 ARTIFICIAL INTELLIGENCE IN MEDICINE

The capacity of a machine or systems to carry out operations that ordinarily support learners, such as learning, dilemma, and decision-making, and support is known as artificial intelligence (AI) [13]. The detection, cure, and illness prevention are just a few of the areas of healthcare that AI has the potential to improve. AI can be used in medicine to evaluate vast volumes of data, including medical records, imaging studies, and laboratory test results, to spot patterns and trends that a human eye might miss [14]. This can aid medical professionals in making more accurate diagnoses and treatment choices. AI can be utilized to develop predictive models that assist in identifying individuals who have a higher likelihood of developing specific diseases or disorders such as diabetes or heart disease. As a result, healthcare professionals may be able to take precautions to lower the chance of developing certain disorders [15].

The processing and analysis of medical data, for example, can be automated using AI, which can lessen the strain of medical practitioners and increase the effectiveness of healthcare systems. All things considered, using AI to medication has the potential to enhance quality of care, lower costs, and widen access to healthcare. Nonetheless, during using, there are also moral and legal considerations to make. AI in healthcare, including data privacy and algorithmic bias. To ensure that the use of AI in medicine is morally and responsibly, it is crucial to give these concerns significant thought. Regarding the application of AI in medicine, the following extra factors should be taken into account: AI in medicine needs to depend on machine learning, which is a computer or machine's capacity to pick up new skills and enhance performance without being explicitly taught. ML algorithms examine data, learn from it, and then use the connections they find to forecast or decide. The diagnosis, treatment, and prevention of diseases are just a few of the areas in which AI has the potential to change healthcare. One of the main advantages and developments of AI within medicine is:

Increased precision: AI systems can examine vast amounts of data and spot patterns and trends that a human eye might miss. This can aid medical professionals in making more accurate diagnoses and treatment choices.

Customized medicine: AI can be used to develop personalized treatment plans based on an individual's specific medical history, risk factors, and other data. This can help improve the effectiveness of treatment and increase patient satisfaction.

Early detection: AI can be used to develop predictive approaches that able identify people who are at high risk for certain diseases or conditions. This can allow healthcare providers to take preventative computes the risk percentage of these illnesses.

i. Increased efficiency: Certain operations, such collecting and interpreting medical data, can be automated by AI, which can lessen the strain of healthcare providers and increase the effectiveness of healthcare systems. .

ii. Drug development: AI can be employed to analyse vast volumes of data to find patterns and trends that could be helpful in the creation of novel medications or treatments. This could hasten the process of developing new drugs and produce the desired results.

iii. Telemedicine: Telemedicine, which enables healthcare providers to give medical care online, can be supported by AI. People who live in underserved or distant places may have easier access to healthcare as a result. There are still numerous unrealized potential advantages and advancements in the field of AI in medicine. AI is anticipated to serve a bigger and bigger part in the healthcare sector as it continues to advance and grow.

iv. Predictive analytics: AI can be used to develop predictive models that can help identify people who are at high risk for certain diseases or conditions. These models can analyze data from electronic medical records, imaging studies, and laboratory test results, among other sources, to identify patterns and trends that may indicate a higher risk of a particular disease or condition.

v. Diagnostic assistance: Artificial intelligence (AI) can be used to examine X-rays and MRIs to find anomalies or problems that may not be initially visible to a human eye. This can aid medical professionals in making more precise diagnosis and creating effective treatment regimens.

vi. Treatment planning: AI can be used to help develop personalized treatment plans based on an individual's specific medical history, risk factors, and other data. For example, AI algorithms can analyze data from electronic medical records and laboratory test results to help identify the most effective treatment options for a particular patient.

vii. Drug development: AI can be used to examine vast volumes of data to find patterns that could be helpful in the creation of novel medications or treatments. AI systems, for instance, can examine information from clinical trials and other sources to find possible therapeutic targets or forecast the efficacy of a specific medication or medication.

viii. Ethical and legal considerations: There are a number of ethical and legal considerations to

2.9 MACHINE LEARNING

In the branch of artificial intelligence known as "machine learning," algorithms and statistical models are used to help a system become better at a given activity over time. In machine learning, a system is trained on a dataset before being used to generate predictions or conduct actions. The system "learns" to optimise its performance on the specified job by repeated exposure to the data. Predictive analytics, speech recognition, computer vision, and other industries all heavily rely on machine learning. The development of self-driving cars, virtual personal assistants, and many other cutting-edge technology has also relied on machine learning, which is a potent tool for addressing a wide range of practical issues. Some examples of the applications of machine learning include language recognition, fraud detection, and customer relationship management. A well-known application of machine learning is the categorization of email messages as spam or non-spam. The performance of machine learning in this case is measured by the percentage of emails that are correctly classified. Machine learning has proven to be effective in this and many other tasks, and its use is expected to continue to expand in the future [16].

2.9.1 Supervised learning

It entails building a model on a labelled dataset, where each sample in the training data is given the right output. Building a model that can generate accurate predictions for brand-new, unforeseen data is the aim of supervised learning. Classification tasks, like determining if an email is spam or not, and regression tasks, like estimating the worth of a place based on its attributes, are examples of supervised methods [17].

2.9.2 Unsupervised Learning

It includes building a model on an unlabelled dataset in which not every example in the training data has the expected result. Instead of generating predictions, the aim of unsupervised learning is to uncover structures or relationships in the data. Clustering, which is used to group similar occurrences together, and data preprocessing, which is used to reduce the number of features in the data, are two instances of unsupervised learning [18].

2.9.3 Reinforcement Learning

A model must be trained to make judgements in a dynamic setting with the objective of maximising a reward signal. The model picks up new skills through trial and error, getting feedback based on its deeds that may be favourable or unfavourable. Reinforcement learning is used by autonomous robots like self-driving automobiles as well as game-playing agents like computer programmes that play Go or Chess [19].

2.10 CNN

Medical image classification is crucial for clinical care and education, but conventional approaches are no longer effective. Additionally, extracting and choosing classification features using these methods takes a lot of time and work. CNN, a subset ofDL models, have demonstrated significant promise in a number of classification tasks [20]. DL algorithms such as CNN are designed specifically for image processing jobs. Several interconnected layers make up a CNN, which perform and examine input data. The CNN's structure is made up of a variety of various levels [21]. A CNN has various kinds of layers, including:

i. Convolutional layers: T Convolutional filters are applied to the input data by these layers, aiding in the feature extraction process from the images.

ii. Pooling layers: These layers downsize the feature maps produced by the convolutional layers to lessen the computational load and increase the model's capacity for generalisation.

iii. Fully connected (FC) layers: These layers perform classification or regression by computing the dot product between the input data and a set of learned weights.

iv. Activation layers: These layers apply a nonlinear function to the outcome of the previous type of layerin order topropose nonlinearity into the model.

v. Normalization layers: These layers help to boost the generalization ability of the model by normalizing the activations of the previous layer.

vi. Dropout layers: These layers help to prevent overfitting by randomly setting a fraction of the activations of the previous layer to zero during training.

vii. Recurrent layers: These layers add feedback connections to the network, enabling the model to process sequential data.

In conclusion, the literature review on spinal tumor detection using CNNs has shown that this approach has the potential to be an effective tool for accurate and efficient detection of spinal tumors. Future research may focus on addressing these challenges and further evaluating the performance and clinical utility of CNN-based approaches for spinal tumor, generally medical images detection.

3. PROPOSED METHODOLOGY

3.1 INTRODUCTION

In this chapter, we introduce a new model for detecting spinal tumorsusing a convolutional neural network, MobileNet and DensNet. At first, we will introduce the proposed model and thoroughly describe the all the layers related to detect the spinal tumor using CNN, MobileNet and DensNet.

3.2 PROPOSED MODEL FOR SPINAL TUMOR

Our proposed model for spinal tumor detection is used three deep learning methods like CNN, MobileNet, and DenseNet. The aim of the model is to precisely identify tumors in spinal cord imaging and improve the accuracy and effectiveness of spinal tumor identification. The process of creating the proposed model involves several key steps, starting with the collection and pre-processing of a dataset of MRI scans of the spinal cord. Next, the network architecture is designed and implemented, using existing deep learning models to make the final prediction. The model is then trained on the pre-processed dataset, with performance monitored and adjusted as necessary. Once the model has been trained, it is evaluated on a test set using common metrics.

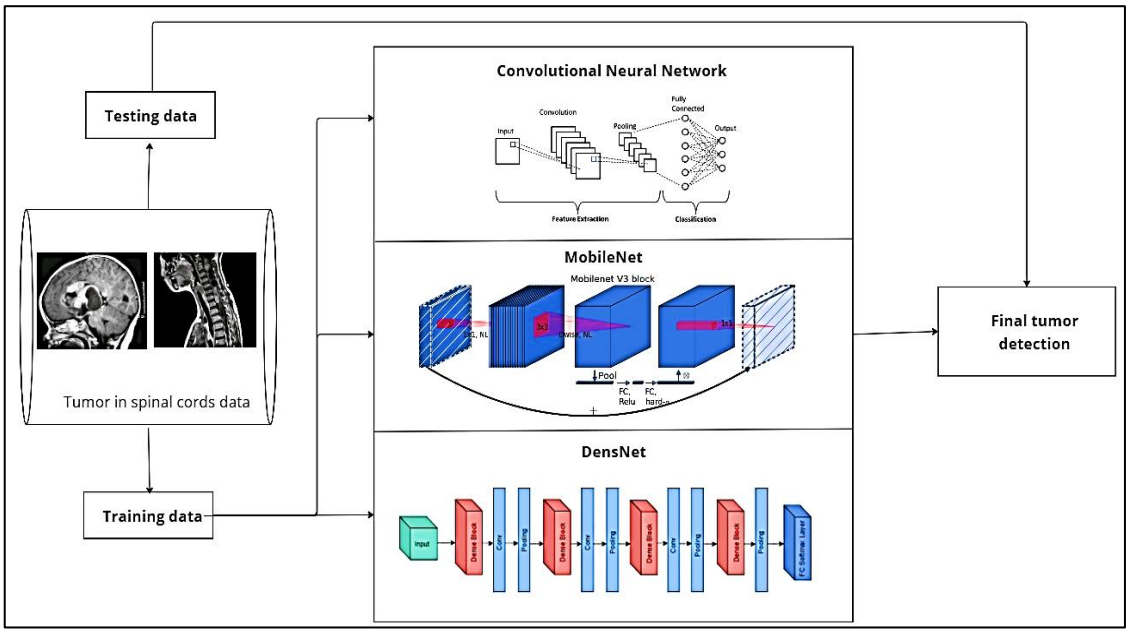

Figure 3.1: Flowchart of Our Proposed Model For Spinal Tumor.

3.2.1 Convolutional Neural Network for Spinal Tumor

CNN have gained popularity for detecting tumors in the field of medical image processing for detecting tumors. These deep neural networks are designed specifically for interpreting visual information and have been widely researched and developed over the years. While traditional fully connected neural networks can also be used for this purpose, CNNs have been favored due to their ability to share parameters and have sparse connections, resulting in improved accuracy and efficiency in detecting tumors.

CNN has been developed and applied for the detection of tumors. The network is composed of multiple layers, including convolutional layers, pooling layers, flattening layers, and a fully connected layer, in addition to the input and output layers. These layers work together to provide a better performing model for the detection of tumors.

The methodology for tumor detection in spinal cords using Convolutional Neural Network is presented in Figure 4.1.

In the following section, we will delve into the characteristics of each layer in the network.

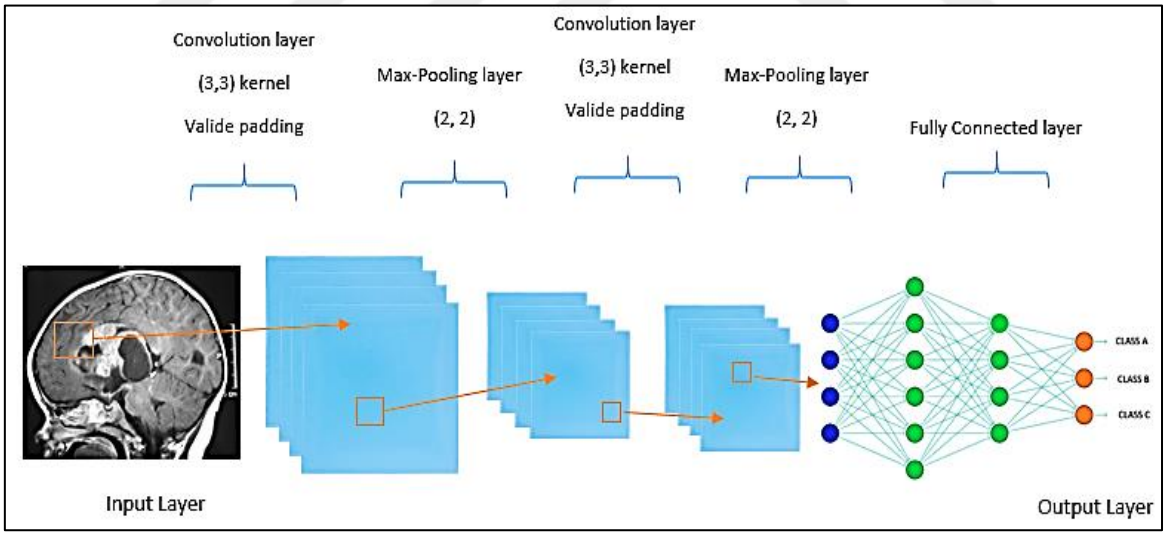

Figure 3.2: Convolutional Neural Network For Tumor Detection in Spinal Cords.

3.2.1.1 Convolutional layer

A Convolutional layer is a crucial component of CNN models. It acts as the starting point for processing and transforming the input data, in this case, MRI images, into a consistent

format. The convolutional layer takes the input shape of the MRI images and applies a convolutional kernel, consisting of 32 filters of size 3x3, to produce a feature map. The activation function used in this layer is the Rectified Linear Unit (ReLU), which helps introduce non-linearity into the model.

The evaluation of a Convolutional Neural Network model often involves adjusting three important hyperparameters: depth, stride, and zero-padding. In the case of this specific model, the input volume has a size of 224x224x3 and the filter size used is 3x3 with a spatial extent of 3. No zero-padding was utilized, and the stride value was set to 1. In the model, all spatial downsampling with a stride of 1 occurs in later pooling layers, allowing the CONV layers to only adjust the depth of the input. After applying the convolutional layer equation (4.1), the dimensions of the convolutional layer were determined to be 222x222x32. The second layer in the model was a max pooling layer, introduced after the convolutional layer.

$$\text{Conv\_output\_size} = (\text{input\_size} - \text{filter\_size} + 2 * \text{padding}) / \text{stride} + 1 \quad (3.1)$$

3.2.1.2 Max pooling layer

In a CNN, the pooling layer's main objective is to gradually reduce the spatial dimensions of the representation in order to streamline the network and lower its processing requirements. By lowering the amount of network parameters, this decrease aids in the management of over-fitting. In particular, the max pooling layer reduces the input's spatial dimensions by independently operating on each depth slice. As a result, the complexity of the network can be decreased while still maintaining the representation's key details.

When working with spinal tumor images, it is important to prevent over-fitting, which can negatively impact the accuracy of the model. The proposed model uses a Max Pooling layer to decrease the spatial dimension of the representation. The input size of the image is 222x222x32, and after applying the max pooling layer using equation (4.2), the output volume size was calculated to be 111x111x32. The pool size used in the model is (2, 2), meaning the input is down-scaled by a factor of 2 in both the vertical and horizontal dimensions. This helps to simplify the network and control over-fitting by reducing the number of parameters that need to be trained.

$$\text{Pool\_output size} = (\text{input\_size} - \text{pool\_size}) / \text{stride} + 1 \quad (3.2)$$

3.2.1.3 Flatten layer

After the pooling layer, a pooled feature map is produced. To prepare the feature map for further processing by the Neural Network, it is necessary to use a Flatten layer. This layer transforms the matrix representation of the input images into a single column vector. The Flatten layer is essential for processing the data within the Neural Network. Its dimension is calculated as 222x222x32 = 12,664,064. This one-dimensional vector serves as the input to the Neural Network for analysis and prediction.

3.2.1.4 Fully connected layer

Our model incorporates two fully connected layers. These layers were implemented using the "dense" function in Keras to facilitate processing within the neural network. The output from the previous step was input into these dense layers for further analysis and prediction.

In our model, the hidden layer was configured with 128 nodes. The size of a layer impacts the computational resources required to fit the model, thus a moderate amount of nodes was selected to ensure optimal efficiency. 128 nodes were selected because it produced the best results while maintaining reasonable computational requirements.The activation function applied in this layer was ReLU, which demonstrated improved convergence performance compared to other activation functions.

The second fully connected layer served as the final layer of the model. A softmax activation function was utilized in this layer with a single node.The use of a softmax activation function and only one node was a conscious design decision aimed at reducing computational requirements and speeding up execution time. However, there is a risk of hindering the learning process in deep networks with the use of a softmax activation function. To mitigate this risk, the softmax function was scaled down, and the number of nodes was kept to a minimum, making it easier to handle for this deep network.

3.2.2 MobileNet for Spinal Tumor

MobileNet is a deep learning network optimized for mobile devices and other systems with limited computational power [27]. MobileNet utilizes depthwise separable convolutions to lower the quantity of parameters and computation required. As a result, MobileNet is faster

and more efficient than traditional CNNs. It is frequently employed in computer vision applications such as image classification, object detection, and semantic segmentation.

MobileNet can be used in medical imaging applications, including the detection of spinal tumors. By training a MobileNet model on a dataset of spinal MRI scans, it is possible to develop a deep learning algorithm that can automatically detect and classify spinal tumors.

The MobileNet architecture is based on the concept of depthwise separable convolutions. It consists of a series of convolutional and pooling layers, followed by a few fully connected layers. The key feature of MobileNet is the use of depthwise separable convolutions, which breaks down a standard convolution operation into two separate operations: depthwise convolution and pointwise convolution. The depthwise convolution operates on each channel of the input independently, while the pointwise convolution combines the outputs from the depthwise convolutions to produce the final output. This allows for a reduction in the number of parameters and computation required, making the network more efficient.In addition to depthwise separable convolutions, MobileNet also employs a number of other techniques to further reduce the computational cost of the network, such as using smaller kernel sizes, reducing the number of output channels, and using strided convolutions.

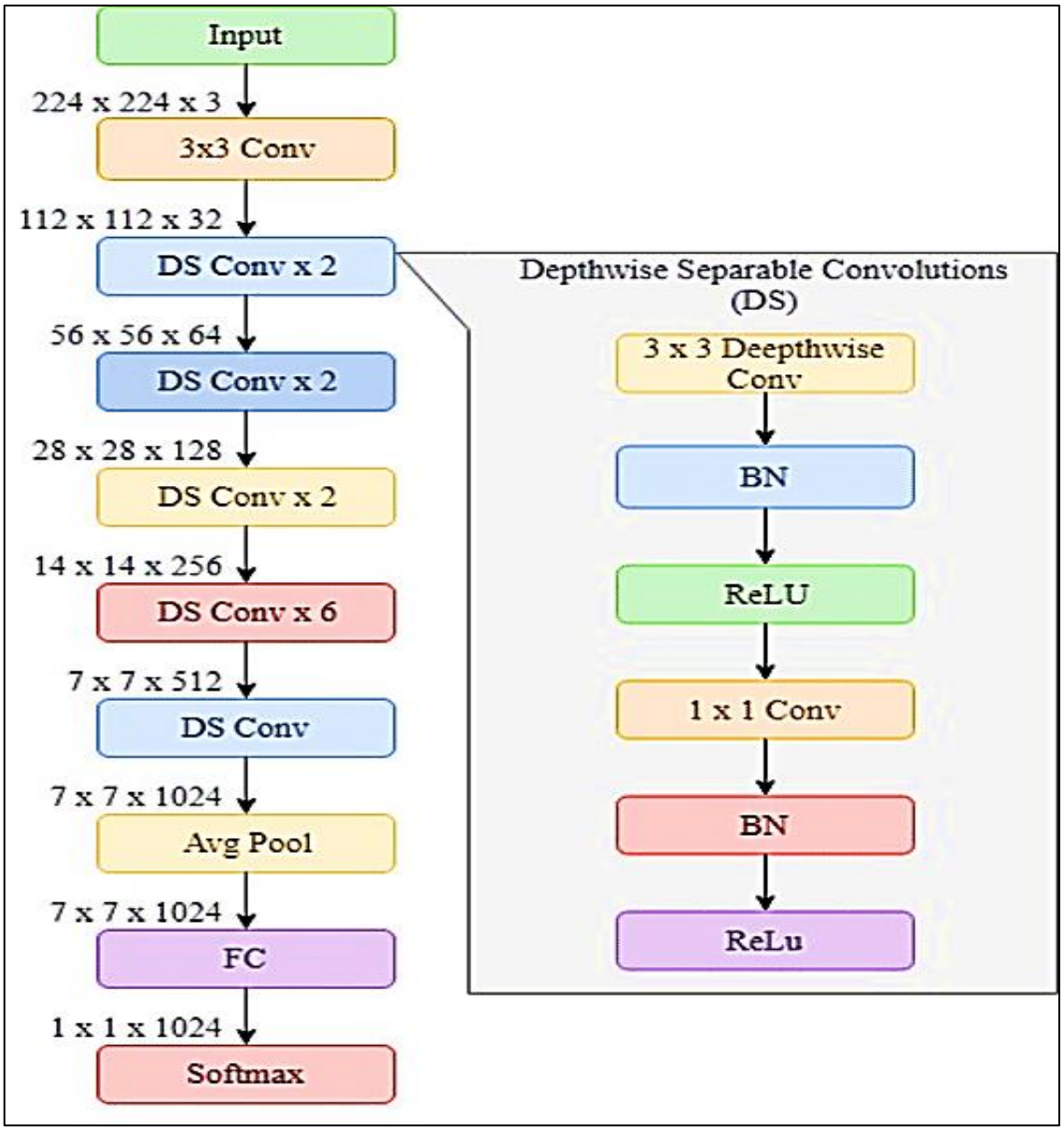

Figure 3.3: MobileNet Architecture [22]

By adding a series of dense layers to the MobileNet architecture, wecreating a new deep learning model that combines the feature extraction capabilities of MobileNet with the prediction capabilities of fully connected layers. The dense layers take the processed feature maps from the MobileNet as input, apply a series of matrix operations to produce a set of activations, and use these activations to make predictions. The addition of dense layers to MobileNet allows the model to learn higher-level features from the input data, and make predictions based on these features.

The new architecture consists of a series of dense layers with different number of neurons, followed by dropout layers to prevent overfitting. The final layer has a number of neurons

equal to the number of classes in the output and a softmax activation, which produces a probability distribution over the classes. The architecture is compiled with an optimizer, a loss function, and evaluation metric, and is ready to be trained on your data.

3.2.2.1 Depthwise convolution

Deep learning uses a particular kind of convolution technique called depthwise convolution. Each channel of the input is subjected to a filter as part of a conventional convolution operation to create a feature map. In contrast, a depthwise convolution produces numerous feature maps by applying a different filter to each input channel. When compared to a regular convolution, the depthwise convolution is computationally efficient because it functions independently on each channel.

The network is made faster and more effective by using depth-wise convolutions to reduce the amount of parameters and computation needed. They are also utilized in various neural networkarchitectures to enhance the network's performance, particularly when it is installed on computers with limited resources.

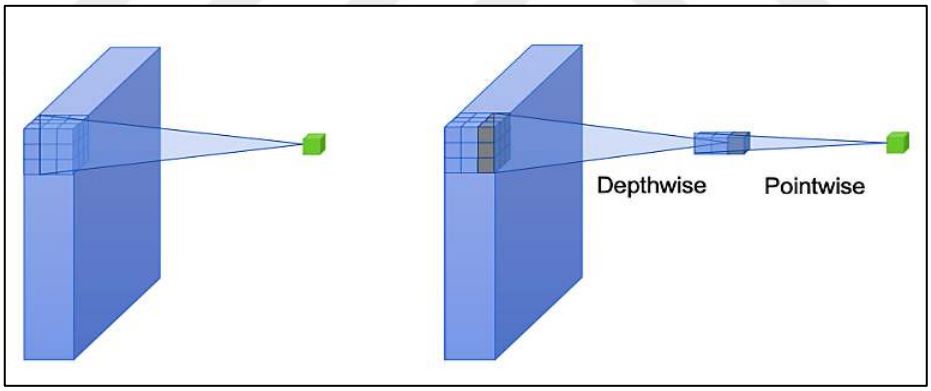

Figure 3.4: Separable Dilated Depthwise Convolution [62]

3.2.2.2 Pointwise convolution

Pointwise Convolution is a type of convolution operation that is applied independently to each input element (point), rather than being performed over a sliding window of multiple input elements as in standard convolution. In other words, Pointwise Convolution uses a set of filters of size 1x1 to process individual input elements [28]. This kind of convolution is utilized in multiple computer vision and deep learning applications to decrease the spatial dimensions of the input data while increasing the number of channels.

a. The procedure is iterated multiple times, with each iteration utilizing the output of the previous one as its input. The final output is obtained through the use ofdepthwise separable convolutions and pointwise convolutions in each iteration.

3.2.3 DensNet for Spinal Tumor

The DenseNet architecture is characterized by dense connectivity between layers [24]. This means that each layer receives input from all previous layers, rather than just from the immediately preceding layer. This enables a more efficient flow of information and reduces the number of parameters in the network.

In a DenseNet, the output of one layer serves as input to all subsequent layers, which leads to a so-called dense block. Within a dense block, the layers are concatenated along the channel dimension, allowing the network to propagate rich feature representations through the network.

A crucial aspect of the DenseNet architecture is the utilization of transition layers, which decrease both the spatial dimensions and number of channels between dense blocks. This helps to alleviate the vanishing-gradient problem and improve the flow of gradients during training. Finally, the network is typically topped off with one or more fully connected layers for making the final predictions.

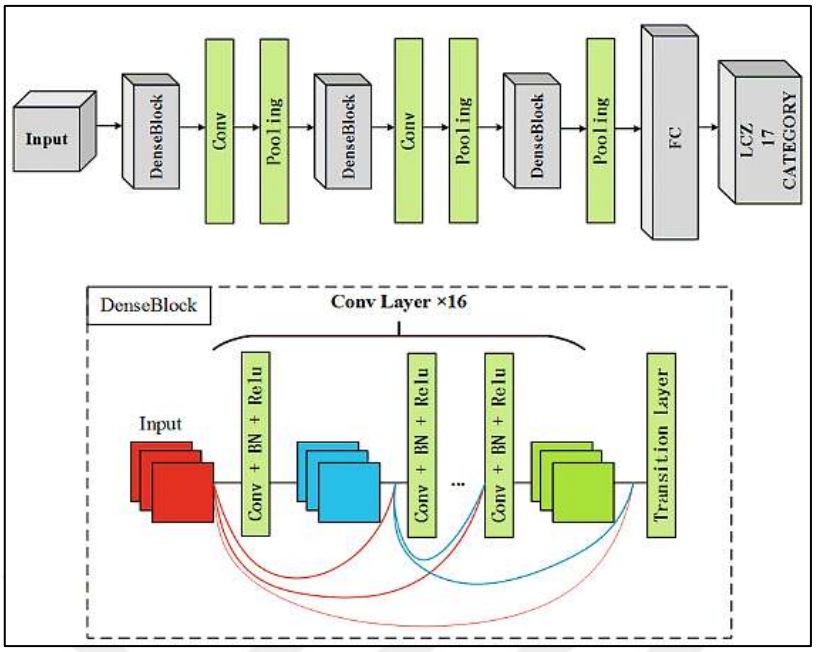

Figure 3.5: DensNet Architecture [23]

Adding a dense layer to the DenseNet architecture results in what is known as a hybrid architecture. The dense layer would serve as a fully connected layer, which means that every neuron in the dense layer would be connected to every neuron in the preceding layer.

This hybrid architecture would combine the strengths of both the DenseNet and dense layer architectures. The dense connectivity pattern of DenseNet would allow for effective information flow throughout the network, while the dense layer would add a non-linear mapping that can learn complex representations of the input data.With the addition of the dense layer, the network would be able to make predictions based on a combination of low-level and high-level features extracted from the input data. This can lead to improved performance on tasks such as image classification or object detection.

3.2.3.1 Dense block

A dense block is a key component of the DenseNetarchitecture[25]. A dense block contains multiple layers that are densely connected, meaning that each layer receives input from all previous layers within the same dense block, rather than just the immediately preceding layer.

The dense connection pattern of the dense blocks facilitates effective information flow and helps to decrease the number of parameters in the network. The layers within a dense block are concatenated along the channel dimension, allowing the network to propagate rich feature representations throughout the network.The number of layers within a dense block, as well as the number of dense blocks within the network, can be varied to control the model capacity.

A basic block in the system consists of four layers applied to a concatenated input: Batch Normalization, ReLU activation, a 3x3 convolutional layer with stride of 1 and zero padding, and Dropout with a rate of 0.2. The convolutional layer uses k filters [26].

3.2.2.2 Transition layers

Transition layers are a key component of the DenseNet architecture. They serve as bridges between dense blocks and are used to reduce the spatial dimensions and the number of channels in the network.The main purpose of transition layers is to alleviate the vanishing-gradient problem that can occur when training deep networks. By reducing the spatial dimensions and the number of channels, transition layers help to improve the flow of gradients during backpropagation, allowing the network to be more efficiently trained.A typical transition layer consists of a batch normalization layer followed by a convolutional layer with a stride of 2, which halves the spatial dimensions. The number of filters can also be reduced to further control the complexity of the network [26].

In addition to improving the flow of gradients, transition layers also help to control the model capacity and reduce the risk of overfitting. By reducing the spatial dimensions and the number of channels, the network becomes less prone to overfitting, as it has fewer parameters to fit to the training data.

3.3 CONCLUSION

In this chapter, the proposed methodologydetection of tumor in spinal cords is described. We used CNN, MobileNet and DensNet to detect tumor in spinal cords. In the next chapter, we will describe the implementation details of our model to evaluate the performance.

4. RESULTS AND DISCUSSIONS

4.1 INTRODUCTION

In this section, we will provide a comprehensive analysis of our proposed methodology outcomes. We utilized a spinal tumor dataset and classified samples as Meningioma, Glioma, or Pituitary tumors using deep learning techniques such as CNN,Mobilenet, and Densenet. After that, we will evaluate the models performance and compare their results. Additionally, we will compare our model's classification accuracy to existing models.

4.2 DATASET DESCRIPTION

In our proposed system, we used images of tumors in spinal cords that were classified by specialist physicians. We applied various image processing techniques and employed artificial neural networks to classify these images. Our goal is to provide a reliable and efficient automated system for medical practitioners to make accurate diagnoses of spinal tumors at different stages. The system aims to facilitate early detection of spinal tumors, thereby reducing the number of related fatalities.

In this study, experiments will be carried out on the database images to evaluate the proposed topology. Different parameters of image processing and neural networks will be used in each experiment. Figure 4.1 displays the images in the dataset. The original images are first retrieved from the database and resized to reduce processing time. The processed images have a size of 224*224. The database images are then converted to gray scale, where colors are represented on a scale between white and black. These images offer efficient processing while maintaining the same performance as colored images, as computers do not recognize colors. The processing of grayscale images is three times faster than processing their RGB versions.

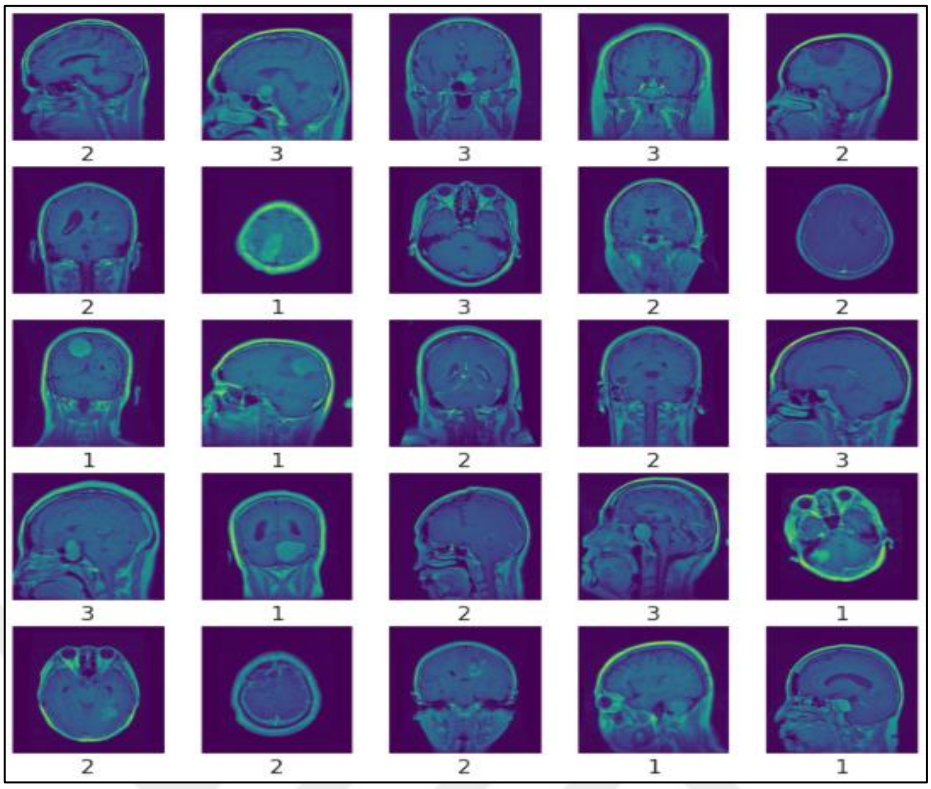

Figure 4.1: Some Examples of Images of the Dataset.

Two sets of images were created from the total dataset. The suggested backpropagation method was trained on one group, while the performance of the trained network was tested on the other. The testing process was designed to evaluate the network's ability to correctly identify unfamiliar images from the training set. This is a crucial aspect of the neural network, as it should demonstrate generalization for images outside the training database. After each stage of image processing, a neural network was deployed to assess the impact of each processing technique on the network's performance.

4.3 EVALUATION METRICS

In this section, we will evaluate the performance of our model by examining the relevant performance matrices. To thoroughly assess the accuracy of our model, we need to become familiar with the performance metrics that we have chosen to use. This will involve an in-depth understanding of the terminology related to performance evaluation, which is crucial in effectively interpreting the results of our analysis.

4.3.1 Confusion Matrix

The confusion matrix is a crucial tool in evaluating the performance of model. It presents a summary of the number of correct and incorrect predictions made by the classifier, with the actual class labels forming the rows and the predicted class labels forming the columns. The cells of the matrix contain the values that can be used to compute various performance metrics such as accuracy, precision, recall, F1 score, and others. Confusion matrices are primarily utilized for binary classification problems but can also be applied to multi-class problems.The Confusion Matrix comprises four parameters, each of which is explained in Table 4-1.

Table 4.1: Confusion Matrix

Predict value	**Actual value**	
	True Positive (TP) This refers to the number of tumor images that have been accurately classified	**False Positive (FP)** This refers to the number of non-tumor images that have been mistakenly classified as tumor.
	False Negative (FN) This refers to the number of tumor images that have been incorrectly classified as non-tumor.	**True Negative (TN)** This refers to the number of non-tumor images that have been correctly classified.

4.3.2 Accuracy

Accuracy (Acc) is a performance metric used in classification problems to measure the proportion of correct predictions made by a model relative to the total number of predictions. It's calculated as the number of correct predictions divided by the total number of predictions.

$$Acc = \frac{\mathrm{T\,P + T\,N}}{\mathrm{T\,P + T\,N + F\,P + FN}} \tag{4.1}$$

4.3.3 Precision

Precision (pre) is a performance metric that measures the relevance of the information retrieved by a classification model. It is calculated as the ratio of the number of true positive predictions (correctly classified tumor images) to the total number of positive predictions (correctly and incorrectly classified tumor images). The higher the precision, the lower the number of false positive predictions, and the more effective the model is at retrieving relevant information.

$$pre = \frac{\mathrm{T\,P}}{\mathrm{T\,P+F\,P}} \tag{4.2}$$

4.3.4 Recal

Racal is a performance metric used in classification problems to measure the fraction of relevant items that are successfully retrieved by the model. In the context of a binary classification problem, recall is defined as the number of true positive predictions (i.e. the number of tumor images that are correctly classified as tumors) divided by the sum of TP and FN predictions (i.e. the number of actual tumor images).

$$\boldsymbol{Racal} = \frac{\mathbf{T\,P}}{\mathbf{T\,P+F\,N}} \tag{4.3}$$

4.3.5 F1-Score

The harmonic mean of recall and precision is what is known as the F1-Score, a frequently employed performance metric. The F1-score provides a balance between precision and recall, and it reaches its best value at 1 (perfect precision and recall) and its worst value at 0 (completely inaccurate predictions).

$$F1Score = \frac{2\,TP}{2\,TP + FP + FN} \quad (4.4)$$

4.4 HYPER-PARAMETERS SETTING FOR OUR MODEL

The implementation of the model was done using several state-of-the-art deep learning architectures such as CNN, MobileNet, and DensNet. The hyper-parameter values were set during the initialization and training stage to optimize the performance of the model.

4.4.1 Hyper-parameters Setting for CNN Model

In this section, the values of the hyper-parameters used in the initialization and training stages of our CNN model implementation are described. Shown Table 4-2.

Table 4.2: Hyper-Parameter Value of CNN

Parameters	Value
Conv2D	2
MaxPooling2D	2
Dropout	0.8
Dense	2
Karnel size	(3,3)
Pooling size	(2,2)
Activation Function	relu
Activation Function (output)	Softmax
Epoche	20
Batch size	64
Optimizer	Adam
Loss Function	sparse_categorical_crossentrop

4.4.2 Hyper-parameters Setting for MobileNet Model

In this section, the values of the hyper-parameters used in the initialization and training stages of our MobileNet model implementation are described. Shown Table 4-3.

Table 4.3: Hyper-Parameter Value of MobileNet

Parameters	Value
Conv2D	5
AvgPooling2D	1
Dense	5
Dropout	0.1 and 0.5
Activation Function	relu
Activation Function (output)	Softmax
Epoche	20
Batch size	64
Optimizer	Adam
Loss Function	sparse_categorical_crossentrop

4.4.3 Hyper-parameters Setting for DensNet Model

In this section, the values of the hyper-parameters used in the initialization and training stages of our DensNetmodel implementation are described. Shown Table 4-4.

Table 4.4: Hyper-Parameter Value of DensNet.

Parameters	Value
Conv2D	5
AvgPooling2D	1
Dense	5
Dropout	0.1 and 0.5
Activation Function	relu
Activation Function (output)	Softmax
Epoche	20
Batch size	64
Optimizer	Adam
Loss Function	sparse_categorical_crossentrop

4.5 EXPERIMENTAL RESULTS

We employed three Deep Learning Algorithms to classify our model are CNN, MobileNet and DensNet. In our experiment, we divided the dataset into 80 by 20 ratio, where 80% of the data was utilized for training and 20% was reserved for testing purposes

4.5.1 Evaluation of CNN

To evaluate the performance of our CNN, we calculated the overall accuracy, precision, recall, and f1-score metrics, which represent the proportion of correctly predicted tumor images. Our CNN was trained over 20 epochs and the accuracy score and loss of the predicted model were displayed, as illustrated in Figure 4-2.

Figure 4.2: Model Accuracy and Loss For CNN Predictive Ability With 20 Epochs.

The results of a CNN classification model on three different classes: Meningioma, Glioma, and Pituitary Tumor. The evaluation metrics used are precision, recall, and f1-score. Shown Table 4-5.

Table 4.5: Performance of CNN Model.

	Precision	**Recall**	**F1-Score**
Meningioma samples	0.99	1.0	1.0
Glioma samples	0.98	0.99	0.99
Pituitary tumor	0.99	0.96	0.97

For Meningioma samples, the precision is 0.99, recall is 1.00 and f1-score is 1.00, indicating that the model has high precision and recall values, meaning that it correctly classifies almost all Meningioma samples and correctly identifies almost all the actual Meningioma samples as Meningioma.For Glioma samples, the precision is 0.98, recall is 0.99 and f1-score is 0.99, indicating that the model has high precision and recall values for this class as well, meaning that it correctly classifies almost all Glioma samples and correctly identifies almost all the actual Glioma samples as Glioma. For Pituitary tumor, the precision is 0.99, recall is 0.96 and f1-score is 0.97, indicating that the model performs relatively well, but with some room

for improvement, particularly in terms of recall. This means that while the model correctly classifies almost all the Pituitary tumor samples, it may miss some of the actual Pituitary tumors and classify them as something else.

4.5.2 Evaluation of MobileNet

To evaluate the performance of MobileNet model, we calculated the overall accuracy, precision, recall, and f1-score metrics, which represent the proportion of correctly predicted tumor images. The MobileNet model was trained over 20 epochs and the accuracy score and loss of the predicted model were displayed, as illustrated in Figure 4-3.

The results of a CNN classification model on three different classes: Meningioma, Glioma, and Pituitary Tumor. The evaluation metrics used are precision, recall, and f1-score. Shown Table 4.6.

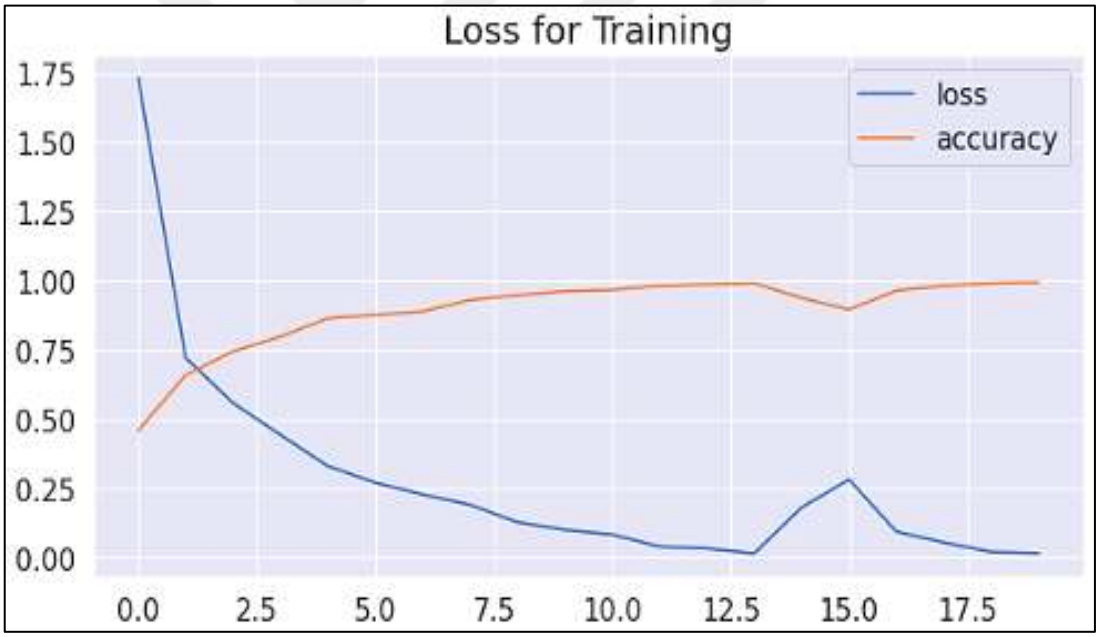

Figure 4.3: Model Accuracy and Loss For Mobilenet Predictive Ability With 20 Epochs.

Table 4.6: Performance of MobileNet Model

	Precision	**Recall**	**F1-Score**
Meningioma samples	1.0	1.0	1.0
Glioma samples	0.99	1.0	1.0
Pituitary tumor	1.0	0.99	0.99

For Meningioma samples, the model has a precision of 1.00, recall of 1.00, and f1-score of 1.00. This indicates that the model has correctly classified all of the Meningioma samples as Meningioma and has a 100% accuracy rate for this class. For Glioma samples, the model has a precision of 0.99, recall of 1.00, and f1-score of 1.00. This means that the model has correctly classified all of the Glioma samples as Glioma, but with a precision rate of 99%, there may be a small number of false positives. For Pituitary tumor, the model has a precision of 1.00, recall of 0.99, and f1-score of 0.99. This means that the model has a 100% precision rate for the Pituitary Tumor class, but with a recall rate of 99%, there may be a small number of false negatives.

4.5.3 Evaluation of DensNet

To evaluate the performance of DensNet model, we calculated the overall accuracy, precision, recall, and f1-score metrics, which represent the proportion of correctly predicted tumor images. The DensNet model was trained over 20 epochs and the accuracy score and loss of the predicted model were displayed, as illustrated in Figure 4-4.

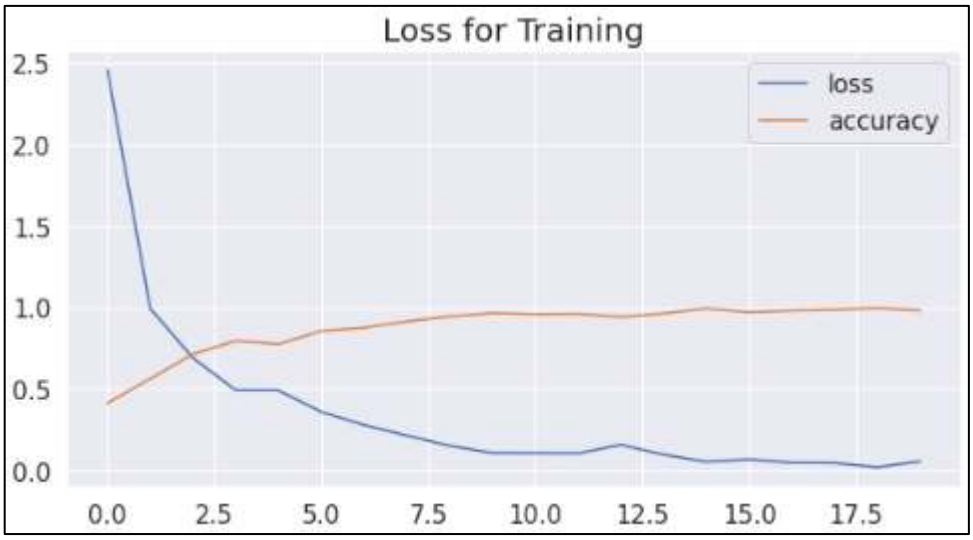

Figure 4 4: Model Accuracy and Loss for Densnet Predictive Ability With 20 Epochs.

The results of a CNN classification model on three different classes: Meningioma, Glioma, and Pituitary Tumor. The evaluation metrics used are precision, recall, and f1-score. Shown Table 4-7.

Table 4.7: Performance of DenseNet Model

	Precision	**Recall**	**F1-Score**
Meningioma samples	1.0	1.0	1.0
Glioma samples	1.0	0.98	0.99
Pituitary tumor	0.96	1.0	0.98

Starting with Meningioma samples, the model achieved a precision, recall, and f1-score of 1.00, which indicates that the model correctly predicted all the Meningioma samples as Meningioma. For Glioma samples, the model achieved a precision of 1.00 and recall of 0.98, with a corresponding f1-score of 0.99. This means that the model had a 100% success rate in correctly identifying Glioma samples, but it had a 2% error rate in identifying all Glioma samples. In the case of Pituitary tumor samples, the model achieved a precision of 0.96 and recall of 1.00, with a corresponding f1-score of 0.98. This means that the model had a 4%

error rate in correctly identifying Pituitary tumor samples, but it had a 100% success rate in identifying all Pituitary tumor samples.

4.5.4 Comparative Results

The results of the three models, CNN, MobileNet, and DensNet, are all very impressive, showing a high level of accuracy in their predictions. Shown Table 4-8.

Table 4.8: Comparisonmodels

Model	Accuracy	Macro Average	Weighted Average
CNN	0.99	0.99	0.99
MobileNet	1.0	1.0	1.0
DensNet	0.99	0.99	0.99

The CNN model achieved an accuracy of 0.99, which is a very high value, indicating that the model makes correct predictions for a high proportion of the total number of samples. The macro average and weighted average of precision, recall, and f1-score were both 0.99, indicating that the model performs well overall across all three classes. MobileNet performed even better, with an accuracy of 1.00, meaning that the model correctly classified 100% of the samples. The macro average and weighted average of the three classes were also 1.00, indicating that the model has an excellent overall performance. Then, DensNet also showed a very high level of accuracy, with an accuracy of 0.99, a macro average of 0.99, and a weighted average of 0.99. This indicates that the model has a very low error rate in all three classes, and has an excellent overall performance.

In conclusion, all three models, CNN, MobileNet, and DensNet, performed very well in the experiment, with all three achieving a high level of accuracy and performing well overall across all three classes.

4.6 CONCLUSION

In this chapter, we presented the performance metrics along with a brief explanation and the values of the hyper-parameters that resulted in the best performance for our proposed model. We demonstrated the experimental results for each class. Lastly, we compared our proposed models.

5. GENERAL CONCLUSION

In our research, we conducted a comprehensive performance analysis of automated tumor detection from MR imaging and CT scans using various image processing techniques that incorporate both hard and soft computing. Additionally, we implemented DL methods specifically for the detection of spinal cord tumors and compared the results of three different DL models: MobileNet, CNN, and DenseNet. Our work presents a systematic approach to tumor detection, which involves the extraction of various tumor features. The results obtained showed that MobileNet had the highest accuracy among the three models.

In order to effectively analyze the full dataset, it is crucial to employ parallel processing and utilize high-performance computing platforms to optimize efficiency. Despite our efforts to accurately detect tumors, we encountered some challenges where tumors were either missed or falsely detected. Therefore, we plan to further investigate these problematic images and the complete dataset. In the future, we aim to implement additional deep learning methods with the goal of obtaining a more precise and improved outcome.

Our thesis work has some limitations that we plan to address in future studies. Firstly, our analysis was limited to two-dimensional images only. This may not accurately capture the full complexity of real-world scenarios, where tumors can have different shapes, sizes, and orientations in three-dimensional space. Secondly, while we utilized deep learning methods in our work, we could have also explored the use of traditional classifiers such as support vector machines (SVMs), decision trees, and random forests to increase accuracy. These algorithms have proven to be effective in a variety of applications and could provide complementary results to those obtained through deep learning methods.

Our thesis work has potential for improvement and further exploration. One way is to enlarge the image sample size for better model training. A larger dataset leads to a more reliable and precise model. Another is to incorporate 3D images for a more complete analysis of tumors in real-world situations. Integrating traditional classifiers such as SVMs, decision trees, and random forests can also enhance accuracy. Our goal is to classify tumors as benign or malignant after detection for medical professionals reference. Lastly, we aim to evaluate different deep learning methods to determine the optimal method for automated tumor detection from medical imaging.

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