

DEEP LEARNING FOR HEALTHCARE SERVICES

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IoT and Big Data Analytics

(Volume 2)

Deep Learning for Healthcare Services

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PREFACE

This book aims to highlight the different applications of deep learning algorithms in implementing Big Data and IoT-enabled smart solutions to treat and care for terminally ill patients. The book shall also unveil how the combination of big data, IoT, and the cloud can empower the conventional doctor-patient relationship in a more dynamic, transparent, and personalized manner. Incorporation of these smart technologies can also successfully port over powerful analytical methods from the financial services and consumer industries like claims management. This coupled with the availability of data on social determinants of health – such as socioeconomic status, education, living status, and social networks – opens novel opportunities for providers to understand individual patients on a much deeper level, opening the door for precision medicine to become a reality. The real value of such systems stems from their ability to deliver in-the-moment insights to enable personalized care, understand variations in care patterns, risk-stratify patient populations, and power dynamic care journey management and optimization. Successful application of deep learning frameworks to enable meaningful, cost-effective personalized healthcare services is the primary aim of the healthcare industry in the present scenario. However, realizing this goal requires effective understanding, application, and amalgamation of deep learning, IoT, Big Data, and several other computing technologies to deploy such systems effectively. This book shall help clarify understanding of certain key mechanisms and technologies helpful in realizing such systems. Through this book, we attempt to combine numerous compelling views, guidelines, and frameworks on enabling personalized healthcare service options through the successful application of Deep Learning frameworks.

Chapter 1 represents a survey of the role of deep learning in the healthcare industry with its challenges and future scope.

Chapter 2 focuses on recent work done in GAN and implements this technique in the different deep-learning applications for healthcare.

Chapter 3 focuses on the role of blockchain in biomedical engineering applications.

Chapter 4 compares three different architectures of Convolutional Neural Networks (CNN), VGG16, and ResNet50, and visually represents the result to the users using a GUI.

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Chapters 5 propose an efficient model for medical image contrast enhancement and correct tumor prediction.

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CHAPTER 1**Role of Deep Learning in Healthcare Industry: Limitations, Challenges and Future Scope****Mandeep Singh^{1,*}, Megha Gupta², Anupam Sharma³, Parita Jain⁴ and Puneet Kumar Aggarwal⁵**¹ *Raj Kumar Goel Institute of Technology, Ghaziabad, India*² *IMS Engineering College, Ghaziabad, India*³ *HMR Institute of Technology & Management, Delhi, India*⁴ *KIET Group of Institutes, Ghaziabad, India*⁵ *ABES Engineering College, Ghaziabad, India*

Abstract: Nowadays, the acquisition of different deep learning (DL) algorithms is becoming an advantage in the healthcare sector. Algorithms like CNN (Convolution Neural Network) are used to detect diseases and classify the images of various disease abnormalities. It has been proven that CNN shows high performance in the classification of diseases, so deep learning can remove doubts that occur in the healthcare sector. DL is also used in the reconstruction of various medical diagnoses images like Computed Tomography and Magnetic Resonance Imaging. CNN is used to map input image data to reference image data, and this process is known as the registration of images using deep learning. DL is used to extract secrets in the healthcare sector. CNN has many hidden layers in the network so that prediction and analysis can be made accurately. Deep learning has many applications in the healthcare system, like the detection of cancer, gene selection, tumor detection, recognition of human activities, the outbreak of infectious diseases, *etc.* DL has become famous in the field of healthcare due to its open data source. In the case of the small dataset, CNN becomes an advantage as it does not provide an excellent way to statistical importance. Deep Learning is a technique that includes the basis of ANN (Artificial neural networks), appears as a robust tool for machine learning, and encourages recasting artificial intelligence. Deep learning architecture has more than two hidden layers, as in ANN; it is only one or two. Therefore, this chapter represents a survey of the role of deep learning in the healthcare industry with its challenges and future scope.

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Keywords: Artificial neural networks (ANN), Auto-encoders (AEs), Bioinformatics, Biological neural networks, Boltzmann machine, Convolution neural networks (CNN), Deep autoencoders, Deep belief networks (DBNs), Deep learning (DL), Deep neural nets (DNNs), Deep structures, Electronic health records (EHRs), Genomics, Machine learning (ML), Medical images, Medical informatics, Pervasive sensing, Restricted boltzmann machines (RBMs), Recurrent neural nets (RNNs), State-of-the-art ML, Unified medical language system (UMLS).

INTRODUCTION

Deep learning has emerged as an interesting new technique in machine learning in recent years. Deep learning, in contrast to more standard Neural Networks (NNs), makes use of numerous hidden layers. A large number of neurons provides a broadcast level of coverage of the initial stage data; the non-linear permutations of the results are in a lower-dimensional projection, and it is a feature of the space. So that every higher-perceptual level is correlated to a lower-dimensional projection. A fine result is given as an effective abstraction at a high level for the raw data or images if the network is suitably weighted. This high level of abstraction allows for the creation of an automatic feature set that would otherwise require hand-crafted or customized features [1]. The development of an autonomous feature set without human interaction has significant advantages in sectors such as health informatics. In medical imaging, for example, it might be more complex and difficult to describe the features by using descriptive methods. Implicit traits could be used to identify fibroids and polyps, as well as anomalies in tissue morphology like tumors. Such traits may also be used to determine nucleotide sequences in translational bioinformatics so that they potentially bind strongly [2]. Several architectures stand out among the numerous methodological versions of deep learning. Since 2010, the number of papers using the deep learning method has increased. It has an interleaved sequence of feedforward layers that employ convolutional filters, followed by reduction, rectification, or pooling layers. Each network layer generates a high-level abstract characteristic [3]. The mechanism allows visual information in the form of related fields and is similar to this physiologically inspired architecture. Deep Belief Networks (DBNs), stacked Auto-encoders acting as deep Auto-encoders, extending artificial NNs with many layers as Deep Neural Nets (DNNs), and extending artificial NNs with directed cycles as Recurrent Neural Nets are all possible architectures for deep learning (RNNs). The latest developments in graphics processing units (GPUs) have also had a substantial impact on deep learning's practical adoption and acceleration. Many of the theoretical notions that underlie deep learning were already proposed before the advent of GPUs, albeit they have only recently gained traction [4].

A new era in healthcare is entering in which vast biomedical data is becoming increasingly crucial. The abundance of biomedical data presents both opportunities and obstacles for healthcare research. Exploring the relationships between all of the many bits of information in these data sets, in particular, is a major difficulty in developing a credible medical tool that is based on machine learning and data-driven approaches. Previous research has attempted to achieve this goal by linking numerous data to create different information that is used in finding data from data clusters. An analytical tool is required based on machine learning techniques that are not popular in the medical field, even though existing models show significant promise. Indeed, due to their sparsity, variability, temporal interdependence, and irregularity, it makes a fine important issue in biomedical data. New challenges are introduced by different medical ontologies, which are used in the data [5]. In biomedical research, expert selection having the composition to employ based on ad hoc is a frequent technique. The supervised specification of the feature space, on the other hand, scales poorly and misses out on new pattern discovery chances. On the other hand, depict learning methodologies allow for the product adaptation of the depictions needed for the prognosis from data sets. Expert systems are a reflection of an algorithm with several presentation levels. They are made up of basic but complex sections that successively change a representation at the beginning level with given input data into and at the end level, a slightly more abstract representation. In computer vision, audio recognition, and natural language processing applications, deep learning models performed well and showed considerable promise. Deep learning standards present the intriguing potential for information related to biomedical, given their established efficacy in several areas and the quick growth of methodological advancements. DL approaches are already being used or are being considered for use in health care [4]. On the other hand, deep learning technologies have not been evaluated for medical issues that are well enough for their accomplishment. Deep learning contains various elements, such as its improved performance, end-to-end learning scheme with integrated feature learning, and ability to handle complicated and multi-modality data, which could be beneficial in health care. The deep learning researchers accelerate these efforts, which must clarify several problems associated with the features of patient records, but there is a need for enhanced models and strategies which also allow transfer learning to hook up with clinical information *via* frameworks and judgment call support in the clinic [5]. This article stresses the essential components that will have a significant effect on healthcare, a full background in technological aspects, or broad, deep learning applications. Conversely, biomedical data is concentrated solely by us, including that derived from the image of clinical background, EHRs, genomics, and different medically used equipment. Other data sources are useful for patient health monitoring, and deep

CHAPTER 2

Generative Adversarial Networks for Deep Learning in Healthcare: Architecture, Applications and Challenges

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Abstract: Deep Learning is a new generation of artificial neural networks that have transformed our daily lives and has impacted several industries and scientific disciplines in recent years. Recent development in deep learning provides various significant methods to obtain end-to-end learning models from complex data. Generative Adversarial Networks give the idea of learning the deep representations without extensively interpreting the training data. The generative adversarial network involves the generative modeling approach that uses the deep learning approach. The chapter is broadly divided into the following sections as (1) Insights of deep learning & the generative adversarial networks, (2) GAN's representative variants, training methods, architecture, and mathematical representation, and (3) Efficacy of GAN in different applications. This chapter will gain the recent work done in GAN and implement this technique in the different deep learning applications for healthcare. Here, we will also analyze some of the future perspectives and trends in the forthcoming time.

Keywords: Deep Learning, Generative Adversarial Networks, Healthcare.

INTRODUCTION

Artificial Neural Networks (ANNs) were used to imitate the biological nervous system in specially designed hardware and software and are now the most trending method in computational intelligence. It has been 70 years now, and ANNs have gained the attention of researchers and are continuing the same. The multilayer neurons have been most widely used at the end of the previous century. The reason for its emergence may include the availability of huge training data-

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sets containing high-quality labels, the emergence of multi-core, multi-threaded implementations, advancements in parallel computing capabilities, *etc.* [1].

The conceptual roots of deep learning are skillfully planted in the traditional neural network composition. Compared to the classical utilization of neural networks, deep learning uses multiple hidden neurons and layers- usually greater than two layers in its architecture combined with the new training methodology that adds an advantage to it. Deep architecture could be built by adding more hidden layers capable of expressing more tedious tasks or hypotheses; it is already known that the hidden layers can easily capture non-linear relationships. The networks formed from the multiple hidden layers are called Deep Neural Networks. Deep Learning provides advanced methods to train deep neural network architectures. Usually, DNN is trained using both supervised and unsupervised techniques. Supervised learning uses class labels to train deep neural networks and determine the weight that reduces the error for predicting a target value and is usually used in classification and regression tasks. In contrast, unsupervised learning uses feature extraction, dimensionality reduction, and clustering methods. Class labels are not provided for training deep neural networks [2].

Researchers of almost every field have actively explored deep learning. Image processing is one among the many. Image super-resolution is an integral part of the image processing techniques that consists of getting a greater resolution image from a lower resolution. This technique is used for various applications, *viz.*, medical imaging, remote sensing, pattern recognition, security, surveillance, *etc.* Many deep learning methods are being used to image super-resolution & image processing tasks that range from traditional convolution neural networks to all new generative adversarial networks [3].

Likewise, Reinforcement Learning is recently gaining a lot of success in solving tedious tasks with continuous control. The deep learning methodology applied in reinforcement learning typically uses multiple function approximators (usually consisting of a network having hidden layers in sharing mode). A new distributional algorithm, C51, was introduced capable of solving the reinforcement learning problem. On top of the methodologies mentioned above, there is also a new way to learn the state-value distribution that is being inspired by the comparison between the actor-critic architecture and the generative adversarial networks [4]. The detail of the above-mentioned techniques will be discussed in the coming sections.

DEEP LEARNING

Deep learning (DL) is part of machine learning with its base in ANN. It is a reliable technique that takes AI to a higher stage and comes up with many advancements. The huge success is the availability of increased computational power, high-speed data storage, and concurrency [2]. The system converts actual data into its feature vector for the machine learning scenario to learn and classify the pattern. In contrast, deep learning involves multiple layers in the learning of complex functions [5]. DL is best for developing intricate structures in multi-dimensional data as it provides complex problem-solving methods in many fields of science, industry, and government. Deep learning started booming in late 2012 as the convolutional neural network (CNNs) gained an overwhelming success in research; researchers and scientists from almost every field started exploring this field [6]. It could be seen that the future of deep learning is promising as it needs significantly less engineering and gives more success by using a vast amount of computational data and novel algorithms and architectures that accelerate its progress [5].

The Transition from Machine Learning to DL

The training methodology in ML can be broadly categorized as supervised and unsupervised learning. A supervised learning approach is used when the output label is already given for the problem set. Here, the training data consists of the numerical or nominal vectors about the features of input data and the respective output data. The training process is defined as the regression when the output is continuous, but when the output data consists of the categorized value, the training process has termed the classification. While unsupervised learning involves unlabeled data, it infers a function that describes the hidden structures. As the data here is not labeled, so one cannot evaluate the accuracy [7]. Naïve Bayes model is typically a classification algorithm that relies on the input data's probability distribution [8]. Among the different classification algorithms, the Support vector machine is the most famous due to its high-performance rank in most related problems [9]. Also, ensemble learning combined with many classification algorithms is being used for precise prediction and more advanced classification [10]. Artificial Neural Network is a popularly known regression and classification algorithm in ML and tries to imitate the signal transmission of the biological nervous system [7]. Fig. (1) gives the conceptual framework of the artificial neural networks derived through natural inspiration. Earlier, the ANN has given an outstanding performance in different fields. Still, it faced several difficulties like local minima while optimizing and overfitting, resulting in deep networks for finding the solution. Deep Neural Networks are formed by the

Role of Blockchain in Healthcare Sector

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Abstract: The domain of bio-medical engineering is facing significant challenges and issues due to data management, data attribution, data security, data availability and privacy. The mechanism of blockchain corresponds to a time-stamped set of data records that is maintained and managed by a cluster/group of the computer system. The collection of cluster groups is secured and protected by cryptographic values, which are often said to be the chains. The growth of blockchain has progressed in a variety of applications in terms of asset management, IoT, smart devices, supply chains, public data validations, and personal identification. Even though the growth has progressed in different emerging disciplines, the impact of blockchain in technology-based biomedical engineering created a vast difference and incorporation in various fields of operation. In a medical data management system, an old audit trail is mostly needed to perform data operations such as insert, delete, and update. Blockchain is, therefore, suitable for the process concerning fixed ledger to record and update critical information services. This chapter completely focuses on the role of blockchain in biomedical engineering applications.

Keywords: Asset management, Biomedical appliances, Data management, Data analytics, Digital medicine, Healthcare infrastructure, Medical data.

INTRODUCTION

Blockchain is one of the continuously increasing applications with a view on significant information and communiqué technology (ICT) and its challenges. It has gained its significance in the field of different sorts of applications such as data analytics, financial sectors, food technology, Internet of Things and Biomedical engineering applications. There exist the most unusual situations and

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forms of applications which efficiently utilize blockchain in the domain of medical applications [1].

Healthcare data management is one of the most essential fields in recent days. Managing and monitoring healthcare data is becoming a tedious process with the rapid generation of data in clinical data analysis. With this consideration, the domain of data-intensive applications such as healthcare data analysis needs a lot of data security and data management service.

In healthcare diagnosis, data management and its confidentiality play a significant role in the patients, doctors and data administrators. The analysis of the correct form of data with the right person and its follow-up has to be maintained to have quality healthcare service.

The improvement in healthcare data analysis has moved to e-health management service with telemedicine facilitation. To manage and transform this into an excellent form of healthcare service, there is a need for blockchain and its functionalities to have a unique and well transferable healthcare service [2]. Upon considering blockchain, the realm of traditional healthcare service can be improved in terms of reliability, safety and security with an impact towards real-time healthcare data analytics.

Biomedical informatics has three significant components in the classification of the data that are intended to develop the decision-support model. Risk analysis and disease prediction in bioinformatics include the applicability of computational techniques to formulate their goal. Informatics techniques such as statistics, machine learning, soft computing, swarm intelligence, data mining, and data visualization have been used by medical data. Hence computational and statistical methods are used to determine the aspects related to a specified disease.

Bioinformatics can be broadly classified into three types based on the type of data to be processed to frame the decision-support model. They are bioinformatics, imaging informatics and public health informatics. The process behind biomedical informatics includes data analysis and data interpretation which are considered to be significant tasks in risk determination.

The platform of bioinformatics includes the process of determining aspects related to gene structure, anticipated properties of diseases, and nucleotide polymorphism structure. The structure provides the determination of disease syndromes with its attribute properties [3]. The protein sequence and its features can be located by the disease specified. The sequential structure of proteins and the organizational structure of nucleic acids can be clearly understood with the processing paradigms and incorporations over bioinformatics. The field of bioinformatics includes the

mechanism of processing a large variety of data based on the type and nature of informatics. It entails the development of algorithms to detect gene structure and its sequence to predict the nature of protein structure and its function-related sequences.

The primary goal behind bioinformatics is to regulate the realization of the biological process. Over the decades, the field of bioinformatics has had its rapid growth over the technological developments in molecular biology. Common research interest in bioinformatics includes the analysis and design of Deoxyribonucleic acid (DNA) sequences, protein sequences and protein structures with 3-D modeling [4].

The health sector needs to be improved by enhancing medical facilities, disease-specific risk factor determination, and by spreading health awareness among the people. In addition to the health sector, there lies an individual responsibility and awareness specific to the disease. Enhancing and rendering health-based services also depend upon the likelihood and habits of the people around a specific region. If the risk-specific syndromes are detected in advance, the cost-effectiveness and treatment expenses can be avoided and thereby, we can render a population-based healthcare service.

Real-time healthcare data analysis involves the process of analyzing and monitoring healthcare records in a real-time perspective and with significant analysis of risk factors and comorbidities [5]. The incorporation of blockchain technology and its functionalities makes the healthcare domain have a good decision support system, and thereby, we can provide a “valuable healthcare service”.

FEATURES OF BLOCKCHAIN

The technology of Blockchain was first explored in the form of bitcoin, which is considered the popular form of cryptocurrency. But, now, it has been explored through various forms of technological incorporations in different fields of action. The following are the features of Blockchain technology which makes it considerable to expose its usage in different fields of action. Decentralized technology, Enhancement in security, faster resolution, compromise, distributed ledgers, and environment cannot be corrupted.

These salient features make blockchain technology to be well adhered towards the domain of medical data analysis and its applications. Since the domain of healthcare needs good and advanced forms of security in order to manage and store data, blockchain can provide a good platform for rendering solutions in a secured way for medical data analysis [6].

CHAPTER 4

Brain Tumor Detection Based on Different Deep Neural Networks - A Comparison Study

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Abstract: Glioblastoma, better known as Brain cancer, is an aggressive type of cancer that is fatal. Biomedical imaging technology now plays a prominent part in the diagnosis of cancer. Magnetic resonance imaging (MRI) is among the most efficient methods for detecting and locating brain tumors. Examining these images involves domain knowledge and is prone to human error. As computer-aided diagnosis is not widely used, this is one attempt to develop different models to detect brain tumors from the MRI image. In this chapter, we have carried out a comparison between three different architectures of Convolutional Neural Networks (CNN), VGG16, and ResNet50, and visually represented the result to the users using a GUI. Users can upload their MRI scans and check the tumor region if they have been diagnosed with cancer. Initially, pre-processed data is taken as input, and the features are extracted based on different model approaches. Lastly, the Softmax function is used for the binary classification of the tumor. To further validate the methodology, parameters like Accuracy, Recall, Precision, Sensitivity, Specificity, and f1 score are calculated. We have observed up to 86% of accuracy in the CNN model, whereas VGG16 and ResNet50 had an accuracy of 100% for our test dataset and 96% for our validation dataset.

Keywords: Bottleneck design, Brain tumor, CNN, Confusion matrix, Contouring, Data augmentation, Data pre-processing, Deep neural network, GUI, MRI images, Residual blocks, ResNet50, Transfer learning, Tumor region, User interface, Vanishing gradient, VGG16, Windows application.

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INTRODUCTION

In biomedical sciences, the conventional approach, identification, and classification for tumor detection are *via* human inspection. Because of the abnormal proliferation of cells in the brain, brain tumors have a negative impact on humans. It has the potential to interrupt genuine brain function and be fatal.

This manual inspection technique is more liable to human error, time-consuming, and in specific instances, very impractical for analysis. Also, the treatment therapy depends upon the tumor's degree at the time of inspection, the pathogenic type, and the tumor's category [1]. With advances in medical and biological imaging technology like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI), detection has become much more effective and precise [2]. In the health care sector, computer-aided technologies for diagnosis, surgeries, and Artificial Intelligence techniques play a significant role. Any analysis of abnormally fast-growing tumor cells needs Automatic Brain tumor segmentation from multimodal MR images [3].

Hence a model with increased efficiency is necessary for the accurate identification of tumors, as computer-aided diagnosis of brain tumors is usually not opted due to the problem of various influencing factors on diagnosis [4]. As a result, the proposed work focuses on correctly recognizing brain tumors and non-tumor MRIs using techniques that remove the tumor from images before applying various deep learning and classification models.

On the other perspective, deep learning is a subsection of artificial intelligence that focuses on model learning from experiences that are based on the data provided to it.

The model's decisions will be based on various input data fed to it during the learning phase. This learning method entails extracting features or patterns from data using the model's algorithm. As new input data is applied to the Neural Network, weights are determined as it moves through the neurons (also known as activation units), which are used to minimize the loss. In addition, hidden layers exist between the input and output layers, which will aid in decision-making. In the final layer, prediction is made on the basis of the model, and weights are calculated. The prediction is then evaluated for accuracy and if this accuracy is acceptable, the model is deployed.

Furthermore, based on our observations, we conclude that the acceptable pixel size should be used to detect the feature or pattern for a given number of hidden layers. This entire procedure is referred to as data pre-processing, and it is a

crucial step before training the classification model. Data augmentation (a form of pre-processing) will be used to improve the model's accuracy.

RELATED WORK

The diagnosis of brain tumors is usually made using imaging data and a brain tumor scan examination. The correct interpretation of these photos is crucial in establishing a patient's status. However, the accumulation of doctors' medical knowledge, differences in experience levels, and evident exhaustion can all affect how well image results are evaluated. Therefore, a way to correctly discover brain tumor scans is very important. Clinical research is aided by the use of PCA-based feature extraction and pattern recognition [5]. This suggests that the entire cerebral venous system is imaged separately using MRI. In layman's terms, a segmenting function is carried out, which is distinguished by a high level of homogeneity between anatomy and adjacent brain tissue. The convolutional neural network classification method has been used to train and test the accuracy of tumor identification in brain MRI images [2].

In terms of delineations, there is a high degree of spatial resemblance and consistency in volume estimates. The strategy beat existing methods for segmenting brain cells not just in terms of volume similarity metrics, but also in terms of segmentation time [5]. A framework for brain tumor segmentation treats the tumor segmentation problem as a machine learning problem [6]. The suggested brain tumor detection method may efficiently detect tumor cells with improved results in terms of correlation coefficient, sensitivity, and specificity, according to experimental data. In comparison to the above-mentioned brain tumor detection approaches, the detection accuracy of a 2D detection network and single-mode is greatly enhanced [7]. Deep Convolutional Neural Networks (Conv-Nets) are being investigated for classifying brain tumors utilizing multi-sequence MR images [8].

The goal is to create an algorithm that makes it easier to extract data from the brain's right and left hemispheres while simultaneously highlighting higher-level statistical features from a different level drawn from the specified brain area. This approach can be used to locate tumor cells using a single spectral magnetic resonance picture [9]. We combined RDM-Net with Deep Residual Dilate Network, which is a residual and dilated convolutional network. It can alleviate vanishing gradient problems while also increasing the receptive field without lowering the resolution. Some knowledge about regions with small tumors could be discarded in image processing, and for resolution, it is diluted to single pixels by going through continuous convolution procedures [10]. Using a Convolutional Neural Network to improve diagnostic outcomes. It primarily segments and

A Robust Model for Optimum Medical Image Contrast Enhancement and Tumor Screening

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Abstract: The use of medical imaging techniques have improved the correctness of disease screening and diagnosis. But, the quality of these images is greatly affected by real-time factors such as the type of machinery used, the position of a patient, the intensity of light, *etc.* The poorly maintained machines, incorrect positioning of patients, and inadequate intensity of light lead to low contrast and poor-quality medical images that work as hindrances in examining medical images. Thus, there is a need to upgrade the features of medical images. Researchers applied histogram equalization for contrast enhancement. However, it improves the visual appearance of medical images but faces the difficulties of over-enhancement, noise, and undesirable artifacts. Also, these techniques report low accuracy in tumor detection. Therefore, we propose an efficient model for medical image contrast enhancement and correct tumor prediction. The model performs segmentation, weighted distribution, gamma correction, and filtering to improve the visual appearance of MRI images. Further, it employs the optimum feature extraction for the correct detection of regions infected with tumors. Furthermore, findings obtained in a simulated environment demonstrate that our proposed model outperforms current models.

Keywords: Automatic, Adaptive gamma correction, Brightness preservation, Brain tumor detection, Contrast enhancement, Convolutional neural network, Deep learning, Entropy, Gray level co-occurrence matrix, Histogram equalization, Homomorphic filtering, Image classification, Model, Medical resonance imaging, Machine learning, Medical imaging, Optimum, Peak signal to noise ratio, Threshold, Tumor, Weighted distribution.

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INTRODUCTION

The mind is the centralized information center of the human body, controlling all functions such as muscle coordination, breathing, metabolism, sense organ functionality, and so on. A brain tumor is an unregulated, unorganized, and undifferentiated mass of cells formed in the brain. It is a potentially fatal illness, and it adversely affects the working efficiency of a person. Among all the ailments, brain tumors are responsible for 85 to 90 percent damage to the central nervous system [1]. Unfortunately, brain and nervous system diseases are the tenth foremost origin of death for both men and women across the globe [2, 3]. It has been estimated that brain tumor is the cause of death of approximately 18,020 people, including 10,190 men and 7,830 women, in the year 2020 [4]. Further, the survival rate of patients is dependent on the age group. The survival rate decreases with an increase in age. The 5-year life expectancy for persons younger than 15 years of age is nearly 74%. Whereas, it decreases to 71% for people of age range from 15 to 39 years and 21% for people of age above 40 years. As per the reports circulated by the “World Health Organization (WHO)” [2], there has been significant growth in the number of brain tumor cases worldwide. In the United States in 2020, 23,890 people, including 13,590 men and 10,300 women, were diagnosed with primary cancerous spinal cord and brain tumors. It is expected that 3,540 youngsters between the ages of 15 would be spotted with a brain tumor by 2021 [5]. The alarming rise in the number of patients and demises due to brain tumor across the world raises the demand for developing the system for early detection and determining the severity of brain tumors.

The symptoms of brain tumor vary based on the affected part of the brain. These symptoms include seizures, headache with vomiting, difficulty in speaking and walking, vision and mental disorders, *etc.* The brain tumor can be categorized into benign and malignant types of tumor. The benign tumor comprises a uniformly distributed mass of non-cancerous cells. Whereas, the malignant tumor consists of a non-uniform mass of cancerous cells. Further, American Brain Tumor Association (ABTA) and World Health Organization (WHO) graded the brain tumor on the measure from I to IV to categorize whether it is benign or malignant [1]. The tumor lies in ranks I and II are categorized as benign tumors while the tumor graded III and IV are classified as a malignant tumor. There are chances that a benign tumor turns malignant if it is not distinguished and treated at the primary phase [1]. As a result, detecting a brain tumor at the earliest point is important.

Many pioneering research works are available for the early finding of the severity of brain tumors from medical images [1 - 5]. But, complex background, the presence of noise in medical modalities, and poor quality of images are the

identified obstacles in the correct and early detection and prediction of tumors from medical images. As a result, image processing technology must be used to strengthen the visual appearance of medical images. These techniques ease the tasks of Machine Learning (ML) and computer vision systems developed for the early screening of tumors. These also improve the visual interpretation, feature extraction, and image analysis efficacy of the ML models.

The literature given from [6 - 20] reveals that HE is the furthestmost used technique for contrast upgrading. This technique uses the cumulative density function and normalizes the intensity dispersal of input image gray levels. It is easy to implement, and accurately and evenly heightens the contrast of an image. Also, it is easy to retrieve the original histogram back from the equalized image. However, this method adjusts an image's mean brightness to the center of the dynamic spectrum. Thus, it creates the problems of over enhancement, increasing the brightness of background noise, and creating intensity saturation artifacts. Further, it focuses mainly on high-frequency histogram bins and eliminates the low-frequency histogram bins that produce the washed-out effects. These limitations are a barrier to the use of HE for medical imaging applications. Also, there are limited research works that proposed an integrated system for refining the feature of medical images and detecting the brain tumor from medical images such as MRI.

To discourse the above-stated limitations, in this chapter, we suggested Robust Otsu's Double Threshold Weighted Constraint Histogram Equalization (ODTWCHE) technique with optimized feature extraction. The overall workflow of the technique is shown in Fig. (1).

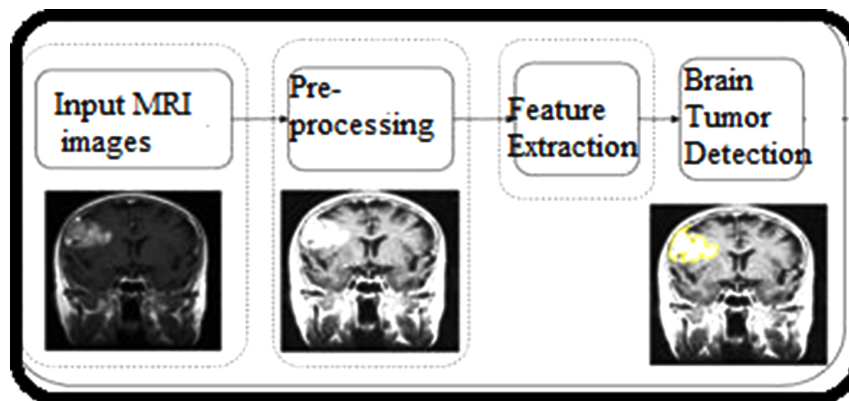


Fig. (1). Activity flow of the proposed model.

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