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Design and Implementing Convolutional Neural Network Modelling for Cancer Classification

A Research

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بِسْمِ ٱللَّهِ ٱلرَّحْمَٰنِ ٱلرَّحِيمِ

(يَرْفَعِ اللَّهُ الَّذِينَ آمَنُوا
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Dedication

To those who brought people out of the darkness of ignorance to the light of guidance is the beloved of our hearts, Messenger of God), may God bless him

My lovely family...

My Supervisor...

My teachers...

My friends...

ABSTRACT

The main purpose of Artificial Intelligence (AI) in clinical medicine is to create a system that can judge medical conditions as accurately as a doctor can. Many medical images are assumed classification as accurately as healthcare experts are when the precision of image detection and recognition in an image processing approach matches that of a human being. Training an artificial neural network (ANN) can assist experts and eradicate possible errors that can arise in several illness classification. As a result, this thesis develops and implements neural network-based methods for cancer classification to expose the neural network's strength in this field.

The term ANN includes some kind of deep learning model. A special computer vision architecture is the Convolutional Neural Network (CNN). it was designed to obtain and process pixel data. Several hyper parameters that control neural network training such as the learning rate and optimization algorithm, must be evaluated to find the best neural network structure that has the best performance in the identification and diagnosis of tumors.

The main aim of this thesis is determine which form of ANN is best for diagnosing human diseases in the terms of speed and accuracy, and to determine the optimum number of layers and neurons in each layer for both forms of CNN and Deep Neural Network (DNN) to obtain the best possible precision.

The proposed methods (CNN and DNN) showed impressive results, especially in CNNs, for both brain tumors skin cancer diseases, and there was a clear superiority of CNN over DNN; The fact that the CNN relies on convolution filters, showed great results in extracting features due to the focus on the intended area of the image without the surrounding area, which led to a remarkable decrease in the number of parameters and the speed of extracting results with higher accuracy. The obtained results indicated that the CNN-based method has a high accuracy rate comparing with the other existing methods where the accuracy rate of CNN and DNN on the same dataset (with 80% training and 20% testing) was 99.60% and 91% for a brain tumor, and 88.0% and 82% for skin cancer.

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List of Abbreviations

Abbreviations	Description
AI	Artificial Intelligent
ANN	Artificial Neural Network
CIFAR	Canadian Institute For Advanced Research
CNN	Convolutional Neural Network
CT	computed tomography
DL	Deep Learning
DNN	Deep Neural Network
FC	Fully Connected
GPU	Graphics Processing Unit
HAM10000	Human Against Machine with 10000 Training Image
IDE	Integrated Development Environment
ISBI	International Symposium on Biomedical Image
ISIC	International Skin Image Collaboration
JPEG	Joint Photographic Experts Group
K-NN	K-Nearest Neighbor
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRI	Magnetic Resonance Imaging
MLNN	Multilayer Neural Network
MCS	Multi-Carotenoids
NLP	Natural Language Processing
PET	positron emission tomography
PNASNet	Progressive Neural Architecture Search
ReLU	Rectified Linear Unit
ResNet	Residual Neural Network
RGB	Red, Green, Blue

SENet	*Squeeze and Excitation Network*
SIANN	*Space Invariant Artificial Neural Network*
SVM	*Support Vector Machine*
TPU	*Tensor Processing Unit*
VGG	*Visual Geometry Group*

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Chapter One

General Introduction

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[illegible]

[illegible]

Medical science currently has an enormous amount of data, including major clinical trials, genomic analyses, and numerous imagery styles. Physicians in the clinical setting should be able to quickly interpret laboratory results and imaging to assess the best treatment plan. Objectively analyzing laboratory data may be done, but also subjectively analyzing image data. The identification of images in medical sciences plays a major role in the classification of images and diagnosis of diseases [1].

The challenge in clinical medicine for Artificial Intelligent (AI) is to develop a system that can as reliably judge medical conditions as a doctor. Medical image analysis is a major burden for physicians and is therefore used to complement the image processing technique [2].

Intelligent tools can enhance disease detection and prevention, and they can be a huge help to physicians. Predictive modeling is an essential part of many healthcare challenges' solutions. It is important to use an alternative method in predicting illness, training an artificial neural network can assist experts and eliminate potential errors that can occur in many illness diagnoses. As a result, this thesis tries to come up with a reasonably efficient solution by developing and implementing a neural network-based system for predicting cancer to reveal the strength of the neural network in this field.

Tumors in the brain can vary from form to texture and place of the tumor based on a few variables. The physicians can identify and anticipate the patient's recovery, depending on the type of tumor, and can also choose a medication that can vary from surgery, chemotherapy, and radionuclides to a wait-and-see plan that prevents intrusive procedures. Therefore, tumor grading is critical in the preparation of treatment and monitoring of care. Magnetic resonance brain image analysis has long been an important area of research, drawing researchers to work on various tasks, such as detecting and dividing lesions, tissue segmentation, and brain segmentation in newborns, infants, and adults [3].

Per year, there are 5.4 million new skin cancers. Early diagnosis of skin cancer is very important because, if detected at the first stages, the average five-year rate of survival falls for more than 99%, although it declines to just around 14% if diagnosed in its late stages [4].

Recently, in several problems for analyzing medical image applications including image segmentation, classification, and de-noising, deep learning (DL's) techniques have played an important part. Convolutional neural networks (CNN) are a type of deep learning architecture that is used lately to perform complex operations that involve the identification of local multi-dimensional features. Convolutional filters have been used in the diagnosis of diseases such as brain tumors and skin cancer, and they have provided higher precision with less complication [5].

[illegible]

A convolutional neural network (sometimes referred to as ConvNet) is a class of deep neural networks used to analyze visual imagery in deep learning [6].The convolution kernels or filters that slide along input features and create translation equivariant responses known as feature maps are based on a shared-weight design, they are often known as Shift Invariant or

Space Invariant Artificial Neural Networks(SIANN). Surprisingly, most CNNs are just equivariant, rather than invariant [7]. Video and Image recognition, financial time series, brain-computer interfaces, natural language processing, recommender technologies, medical image detection, and image segmentation and classification are only some of the areas where they can be used.

When CNN is applied to image analysis, the input is convolved by convolutional layers, which then transfer the output to the layer after. This was motivated by the reaction of the neuron to a particular stimulus in the human visual cortex. In image recognition, a CNN that is well-trained comprises of a hierarchy of details like a corner, edge, a section of an image [8]. A single CNN architecture has several convolutionary layers and pooling layers, with a completely linked layer following them. The main objective of a convolution layer is to abstract features that are learnable from the images, such. The special filter operator parameters, called a convolution, are educated and two inputs are taken for mathematical action, namely an image and a kernel. Visual characteristics can be effectively extracted by learning consequential kernels. The method of convolution can be achieved by using a filter bank where each filter is a squared mesh moving over the input image. Using the weight of the filter the moveable grid image is resumed and several filters are used to construct more functional maps of the convolutionary layer [9].

To achieve completion of image processing operations, Convolution is an essential component of CNN. The map size is reduced efficiently by pooling layers. The object forms and position of the semantic features found in the image are also preserved. Bundling thus reduces the convolutionary layer of the object to minor changes or distortions. In most cases, maximum pooling is used empirically. It is normal to insert periodically the pooling layer between successive convolution CNN layers. The high-level inference of the neural network occurs through completely connected lays after various convolution and pooling layers, which combine all functional answers from the complete image to produce the final output [10].

Compared to other image recognition algorithms, CNN uses very little pre-processing. This allows the network to refine its filters (or kernels) utilizing automatic learning although these filters are hand-designed in conventional algorithms. This freedom from previous experience and human involvement in the extraction of features is a significant benefit [11].

1.3 Related Works

In this section, the study reviews some of the several approaches and methods using image processing technique and deep learning that is used for brain tumor and skin cancer classification systems, some of them are described briefly as follow:

[illegible] [12] focused on the idea that a dermoscopic image containing a skin cancer is classified as normal or abnormal by a specialized problem of skin cancer classification, especially early melanoma identification and a deep-learning approach. The proposed approach is constructed around the neural network model of the VGGNet and uses a framework of transfer learning. The ISBI 2016 Challenge dataset for Skin cancer Analysis towards melanoma detection was used for their experiments. The dataset contains a representative mix of images labeled as benign or malignant, pre-partitioned into sets of 900 training images and 379 test images. Investigational findings are promising; the approach suggested on the ISIC archive reaches a 78.66% sensitivity score, considerably greater than the existing state-of-the-art on the same data set.

[illegible][13] proposed an automatic brain tumor classification system by using CNN to classify the MRI images and diagnose a tumor in the brain. The used dataset contains the tumor and nontumor MRI images and collected from different online resources. Radiopaedia contains real cases of patients, tumor images were obtained from Radiopaedia and Brain Tumor Image Segmentation Benchmark (BRATS) 2015 testing dataset. The enormous amount of information provided by MRI scans thwarts manual tumor vs non-tumor classification at a given time. It does also have some restrictions, which means that a small number of images have to be accurately quantified. During the deeper architecture, small kernels are used. The neuron weight is small. The training precision is 97.5%. Similarly, there is a high validation precision and a very low validation loss.

[illegible][14] proposed a hybrid model (CNN-KNN) for MRI image classification to detect brain tumors. This model integrates CNNs with K-Nearest Neighbor (KNN). In this model, there are 25 layers, 5 of which are Convolution layers and the 1^{st} layer of the model is a dimensional input layer equal to the size of the MRI image. The 2^{nd} layer in this model is a convolutional layer, which applies to the input image a 96 convolutional filter with a size of $11 \times 11 \times 3$, stride 4, and zero paddings. Experiments are conducted on open dataset images chosen from BraTS 2015 and BraTS 2017 database for classification. This model's accuracy was determined to be 96.25%.

[illegible][15] proposed a system that is based on CNN algorithms have been put to use for processing medical imagery and information in contrast to a manual diagnosis of a tumor, which is a tiresome task and involves human error. In general, the functionality is extracted via a CNN, then classified via a fully connected network. A deep neural network approach is used in the framework and a CNN model is incorporated to identify MRI as tumor detected and tumor not detected. A mean accuracy score of 96.08% is obtainable from the model and an F1-score of 97.3%.

[illegible][16] A wide range of methods for detecting skin cancers were studied. They experimented with different neural networks using recent deep learning models such as the InceptionV4, SENet154, InceptionResNetV2, and the PNASNet-5-Large. Tested methods in the 2018 Challenge Data Collection on the International Skin Imaging Collaboration (ISIC). For the PNASNet-5-Large model, the device obtained the best score of 0.76%. It was suggested that improving and optimizing the methods proposed could increase efficiency by using a larger training data set and carefully selected hyper-parameter.

[illegible] [17] Constructed an Artificial Convolutional Neural Networks-based model that analyzes MRI using matrices operations and mathematical formulas. This neural network calculates the probability of the presence of a tumor in the brain, and it was treaned on magnetic resonance images of 98 with tumors and 155 healthy brains. There are 253 magnetic resonance images in total in this dataset. Data augmentation was used to increase its size to 14 times its original size. The model performed exceptionally well in predicting the presence of a tumor, with validation data of 96.7 % and a test rate of up to 88.25%.

[illegible][18] Proposed training two models of CNN and comparing them to determine the best CNN model for classifying tumors in Brain MRI images. The dataset used in this research is Kaggle's Brain MRI Images for Brain Tumor Detection. The dataset contains 253 images divided into two categories: 98 brain images without tumors and 155 brain images with tumors. The result obtained a prediction accuracy of up to 93%.

[illegible] [19] Suggested the diagnosis of brain tumor using MRI images through CNN models. The basis is the Resnet50 architecture, which is one of the CNN models. The Resnet50 model's last five layers were removed, and eight new layers were added in their place. The brain tumor MRI images used in this research came from the Kaggle site's Brain MRI Images for Brain Tumor Detection dataset. There are two directories in the dataset. There are 98 tumor-free images on the first page, while 155 tumor images on the second folder. A precision value of 97.2% is obtained with this model. Googlenet, InceptionV3, Densenet201, Resnet50, and Alexnet models are also collected for results.

Toğaçar, et al. (2020) [20] Brain MRNet is a method that is based on a CNN model as well. Based on care modules and the hyper-column methodology, this architecture features a residual network. First, the image in Brain MRNet is preprocessed. Then, by the image augmentation technique, the effects of this step are passed to attention modules for each image. The image is passed to convolution layers after attention modules choose the main image areas. Hyper-column is one of the most important technology in the convolution layers used by the Brain MRNet model. The array arrangement in the final layer retains the characteristics derived from the individual layers of the Brain MRNet model. The success rate of the Brain MRNet classification was 96.05 %.

[illegible] [21] Because of its optimized architecture and ability to achieve higher accuracy, the ResNeXt101 was proposed as a tool for MCS cancer classification that outperformed all expert dermatologists and contemporary deep learning approaches. The fine-tuning was carried out on seven classes of the HAM10000 dataset, and the performance of five pre-trained convolutional neural networks (ResNetXt101) and four ensemble models was compared. Among the group of models that includes Inceptionv3, InceptionResNetV2, Xception, and NASNetLarge models, the individual model (ResNetXt101) has the highest accuracy of 93.20 percent.

[illegible] (2020) [22]design a system to detect and classify skin cancer with high accuracy and sensitivity by using the Convolution Neural Network (CNN) . The dataset was collected from the International Skin Imaging Collaboration (ISIC). The system is divided into two types which contain the following stages: image acquisition, preprocessing, and classification, while the second part consists of image acquisition, classification. There is a significant change between the classification with preprocessing and without preprocessing, as with preprocessing the accuracy decreased that return to the reason that the pictures that were taken to the skin are too close and do not require any preprocessing. The maximum obtained accuracy was 85.00%.

[illegible]

With the significance of the early and accurate classification of different types of cancers, several of the recent studies rely on Artificial Neural Networks (ANN), according to their outstanding performance in both accuracy and execution time, compared to other techniques. Several methods rely on using the predefined structure of neural networks, e.g., the VGG neural network, or propose a certain structure with a certain number of layers and neurons. However, enhancing the number of layers beyond the complexity of the features to be detected by the neural network to achieve its task increases the complexity of the required computations without implying any improvement to the accuracy. Additionally, the use of a lower number of layers can dramatically reduce the accuracy of the neural network.

Finding the best neural network structure, several of the hyperparameters that govern the neural network training, e.g., the learning rate and optimization algorithm, must be evaluated. This evaluation allows the recognition of the best neural networks with their best performance in tumor detection and diagnosis, according to the significance of such tasks.

[illegible]

This thesis aims to clarify the usefulness of artificial neural networks (ANN) and distinguish which type of ANN is the best in the medical field and diagnose diseases with an accuracy that close the human capacity in terms of speed and accuracy. This achieved by verifying the optimal number of layers and the number of neurons in each layer for both types (CNN and DNN), to achieve the highest possible accuracy and keep model structure complication to a minimum. Besides, the ability to use the recognized features in diagnosing a different type of cancer is also being investigated. Hence, the performance of a specific feature recognized for a particular tumor type is used to detect another type. Then, the same procedure is repeated to discover optimal features and parameters for the other type of cancer, and the difference between performances is clarified and discussed.

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The thesis is segmented into five chapters□ a brief description of their contents is given below□

□□□□□□□ □ □□□This chapter introduces an overview of the work and related works.

□□□□□□□ □□ □□□resents theoretical background for the utilized techniques to detect tumors and cancers, as well as the advantages and disadvantages of using each type of these techniques.

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□□□□□□□ □□□□□Describes the experiments that are conducted to evaluate the proposed systems and validate the hypothesis of this work, in addition to the results collected from these experiments.

□□□□□□□ □□□□Conclusions, and lists some □uggestions for Future □ork.