Analysis of Medical Images using Deep Neural Networks

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***Abstract*—**

Healthcare sector is totally different from other industry. It is on high priority sector and people expect highest level of care and services regardless of cost. It did not achieve social expectation even though it consumes huge percentage of budget. Mostly the interpretations of medical data are being done by medical expert. In terms of image interpretation by human expert, it is quite limited due to its subjectivity, complexity of the image, extensive variations exist across different interpreters, and fatigue. After the success of deep learning in other real-world application, it is also providing exciting solutions with good accuracy for medical imaging and is seen as a key method for future applications in health sector. we discussed state of the art deep learning architecture and its optimization used for medical image segmentation and classification. In the last section, we have discussed the challenges deep learning based methods for medical imaging and open research issue.

***Keywords*— Medical Image analysis, Convolution Neural Network, Health Care, Image Segmentation.**

1. INTRODUCTION

When there was a scarcity of health-care data the data is relatively huge (going to big data) as a result of the significant progress in picture collecting technologies, which makes image analysis tough and exciting. This rapid expansion of medical pictures and modalities necessitates enormous and time-consuming efforts by medical experts, which are subjective, prone to human error, and may differ significantly amongst experts. Using machine learning techniquestoautomatethediagnosisprocessisanalternative answer; however, typical machine learning approaches are unable to cope with complex problems. The ability to cope with large amounts of medical picture data for accurate and efficient diagnosis is promised by the successful marriage of high-speed computers with machinelearning[1-2].

Deep learning will not only assist in the selection and extraction of features, but also in the construction of new ones; further, it will not only diagnose the disease, but will also measure predictive targets and provide actionable prediction models to assist physicians efficiently. In recent years, machine learning (ML) and artificial intelligence (AI) have advanced quickly. Medical image processing, computer-aided diagnosis, image interpretation, image fusion, and image registration have all benefited from machinelearningandartificialintelligencetechniques.image retrieval and analysis, image-guided therapy Machine learning techniques gather information from images and represent it effectively and efficiently. Doctors can use machine learning and artificial intelligence to diagnose and predict illness risks more accurately and quickly, allowing them to prevent diseases before theyoccur.These strategies improve doctors' and researchers' abilities to comprehend how to assess generic changes that lead to disease. Support Vector Machine (SVM), Neural Network (NN), KNN, and other non-learning algorithms are used in these techniques and deep learning algorithms such as Convolutional Neural Network (CNN), Recurrent neural Network (RNN), Long Short-term Memory (LSTM), Extreme Learning Model (ELM), Generative Adversarial Networks (GANs) etc[3-5].

Former algorithms are limited in processing the natural images in their raw form, time consuming, based on expert knowledge and requires a lot time for tuning the features. The later algorithms are fed with raw data, automatic features learner and fast. These algorithms try to learn multiplelevelsofabstraction,representationandinformation automatically from large set of images that exhibit the desired behaviour of data. Although automated detection of diseases based on conventional methods in medical imaging has been shown significant accuracies around for decades, but new advances in machine learning techniques have ignited a boom in the deep learning. Deep learning-based algorithms showed promising performance as well speed in different domains like speech recognition, text recognition, lips reading, computer-aided diagnosis, face recognition, drugdiscovery[6].

2. LITERATUREREVIEW

Over the past decade, Deep Convolutional Neural Networks have been widely adopted for medical image segmentation and shown to achieve adequate performance. However, due to the inherent inductive biases present in the convolutional architectures, they lack understanding of long- range dependencies in the image. Recently proposed Transformer-based architectures that leverage self-attention mechanism encode long-range dependencies and learn representations that are highly expressive. This motivates us to explore Transformer-based solutions and study the feasibility of using Transformer-based network architectures for medical image segmentation tasks. Majority of existing Transformer-basednetworkarchitecturesproposedforvision applications require large-scale datasets to train properly. However, compared to the datasets for vision applications, for medical imaging the number of data samples is relatively low, making it difficult to efficiently train transformers for medicalapplicationshave propose a Gated Axial-Attention model which extends the existing architectures by introducing an additional control mechanism in the

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self-attention module.

Furthermore, to train the model effectively on medical images, [1] have propose a Local-Global training strategy (LoGo) which further improves the performance. Specifically, [1] operated on the whole image and patches to learn global and local features, respectively. The proposed of [1] Medical Transformer (MedT) is evaluated on three different medical image segmentation datasets and was shown that it achieves better performance thanthe convolutional and other related transformer-based architectures.VGG-16 and VGG-19 networks in performing semantic image segmentation of Malaysian meals. [2] made preliminary investigation of using transfer learning models to recognize food objects in typical Malaysian meals. Most current works of food recognition system calculate the calories and nutritional content of a meal based on the food object recognition, regardless of the portion size. The aim of [2] was to develop a food recognition system that considers the portion size in calculatingthecaloriesandnutritionalcontent.Therefore,[2] have presented semantic segmentation of the food objects in the meal which was very important stage. [2] also initiated the training datasets for Malaysian meals that will be made available to the public. Using a small training dataset and a basic configuration of the VGG network, [2] showed inconsistent findings of the performance of VGG-16 and VGG-19. These findings have served as a fundamental guideline to improve the semantic segmentation of food images.

Medical image segmentation is an essential prerequisite for developing healthcare systems, especially for disease diagnosis and treatment planning. On various medical image segmentation tasks, the u-shaped architecture, also known as U-Net, has become the de-facto standard and achieved tremendous success. However, due to the intrinsic localityof convolution operations, U-Net generally demonstrates limitations in explicitly modeling long-range dependency. Transformers, designed for sequence-to-sequenceprediction, have emerged as alternative architectures with innate global self-attention mechanisms, but can result in limited localization abilities due to insufficient low-level details. [3] proposed TransUNet, which merits both Transformers and U-Net, as a strong alternative for medical image segmentation. On one hand, the Transformer encoded by [3] tokenized image patches from a convolution neural network (CNN) feature map as the input sequence for extracting globalcontexts.

Recently, deep learning has become much more popular in computer vision area. The Convolution Neural Network (CNN) has brought a breakthrough in images segmentation areas,especially,formedicalimages.Inthisregard,U-Netis the predominant approach to medical image segmentation task. The U-Net not only performs well in segmenting multimodal medical images generally, but also in some toughcasesofthem.However,[4]foundthattheclassicalU- Net architecture has limitation in several aspects.Therefore,[4] applied modifications: 1) designed efficient CNN architecture to replace encoder and decoder, 2) applied residual module to replace skip connection between encoder and decoder to improve based on the-state-of-the-art U-Net model. Following these modifications, we designed a novel architecture--DC-UNet, as a potential successor to theU-Net architecture. [4] created a new effective CNN architecture and build the DC-UNet based on this CNN. [4] have evaluated our model on three datasets with tough cases and have obtained a relative improvement in performance of 2.90%, 1.49% and 11.42% respectively compared with classical U-Net. In addition, [4] have used the Tanimoto similarity to replace the Jaccard similarity for gray-to-gray imagecomparisons.

3. PROPOSEDMETHODOLOGY

Many image diagnosis tasks require initial search to identify abnormalities, quantify measurement and changes over time. Automated image analysis tool based on machine learning algorithms are the key enablers to improve the quality of image diagnosis and interpretation by facilitating through efficient identification of finding. Deep learning is one extensively applied technique that provides state of the aft accuracy.

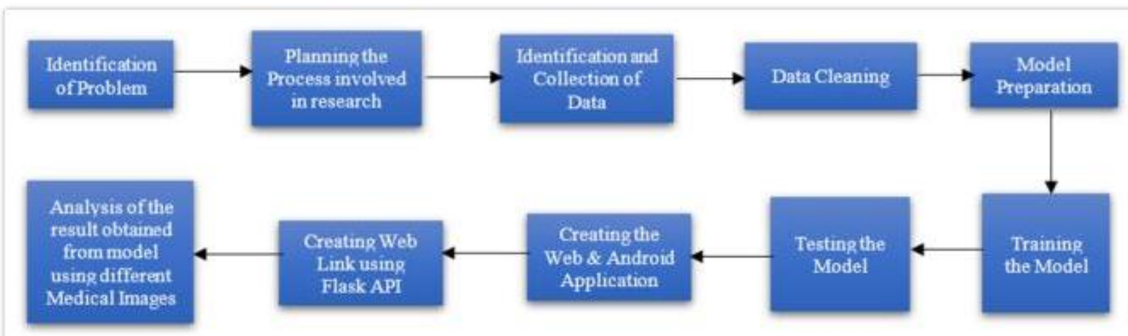

Figure 1: Proposed Framework

It opened new doors in medical image analysis that have not been before. Applications of deep learning in healthcare covers a broad range of problems ranging from cancer screening and disease monitoring to personalized treatment suggestions. Various sources of data today radiological imaging (X-Ray, CT and MRI scans), pathology imaging and recently, genomic sequences have brought an immense amount of data at the physicians disposal. However, we are still short of tools to convert all this data to useful information. In the below discussion, we highlighted state of the art applications of deep learning in medical image analysis

3.1 DataCollection:

Deep learning requires massive amount of training dataset as classification accuracy of deep learning classifier is largely dependent on the quality and size of the dataset, however, unavailability of dataset is one the biggest barrier in the success of deep learning in medical imaging. On the other hand, development of large medical imaging data is quite

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challenging as annotation requires extensive time from medical experts especially it requires multiple expert opinion to overcome the human error.However, dataset been collected from the different diagnostics center and hospital pathology department.

3.2 DataPreprocessing:

For machine learning, we need data. Lots of it. The more we have, the better our model. Machine learning algorithms are data-hungry. But there's a catch. They need data in a specific format. In the real world, several terabytes of data is generated by multiple sources. But all of it is not directly usable. Audio, video, images, text, charts, logs all of them contain data. But this data needs to be cleaned in a usable format for the machine learning algorithms to produce meaningful results. The process of cleaning raw data for it to be used for machine learning activities is known as data pre-processing. It's the first and foremost step while doing a machine learning project. It's the phase that is generally most time- taking as well

Normalization is a systematic approach of decomposing tables to eliminatedata redundancy(repetition)andundesirable characteristics like Insertion, Update and Deletion Anomalies. It is a multi-step process that puts data into tabular form, removing duplicated data from the relationtables.We have Normalize the image by 255 because the image pixels is ranging from 0 to 255, so it is divided by 255 by doing normalization we can fit it into 0 to 1 range.One Hot Encoding: The input to this transformer should be an array-like of integers or strings, denotingthevaluestakenonbycategorical(discrete) features. The features are encoded using a one-hot (aka 'one-of-K' or 'dummy') encoding scheme.This creates a binary column for each category and returns a sparse matrix or dense array (depending on the sparseparameter).By default, the encoder derives the categories based on the unique values in each feature. Alternatively, you can also specify the categories manually.This encoding is needed for feeding categorical data to many scikit-learn estimators, notably linear models and SVMs with the standard kernels.

3.3 ModelArchitecture:

The proposed architecture was built using CNN on various datasetonvariousdiseasesuchasmalaria,retinopathy,brain tumor, breast cancer. The proposed architecture consists of 1 input layer, 7 Hidden layers and 1 outputlayer.

Input layer consist of input shape of the image and for different dataset the input shape was different ranging from 50 to 224.

First hidden layer consists of convolution layer with 32 filters, kernel size 3,3 with activation function 'relu' followed by 2x2 maxpool layer, batch normalization and dropout.

Second hidden layer consists of convolution layer with64 filters, kernel size 3,3 with activation function 'relu' followed by 2x2 maxpool layer, batch normalization and dropout.

Thirdhiddenlayerconsistsofconvolutionlayerwith128 filters, kernel size 3,3 with activation function 'relu' followed by 2x2 maxpool layer, batch normalization and dropout.

Fourth hidden layer consists of convolution layer with 256 filters, kernel size 3,3 with activation function 'relu' followed by 2x2 maxpool layer.

Fourth convolution layer consist of 4-dimension output and dense layer require 2-dimensional output so in between convolution layer and dense layer faltten to be used so that it converts 4D to 2D.

Fifth hidden layer consist of Dense layer with 256 units Sixth hidden layer consist of Dense layer with 128 units.Seventh hidden layer consist of Dense layer with 64 units followed by Dropout

Finally Output layer consist of two units with sigmoid function which helps in predicting two class namely infected and un-infected

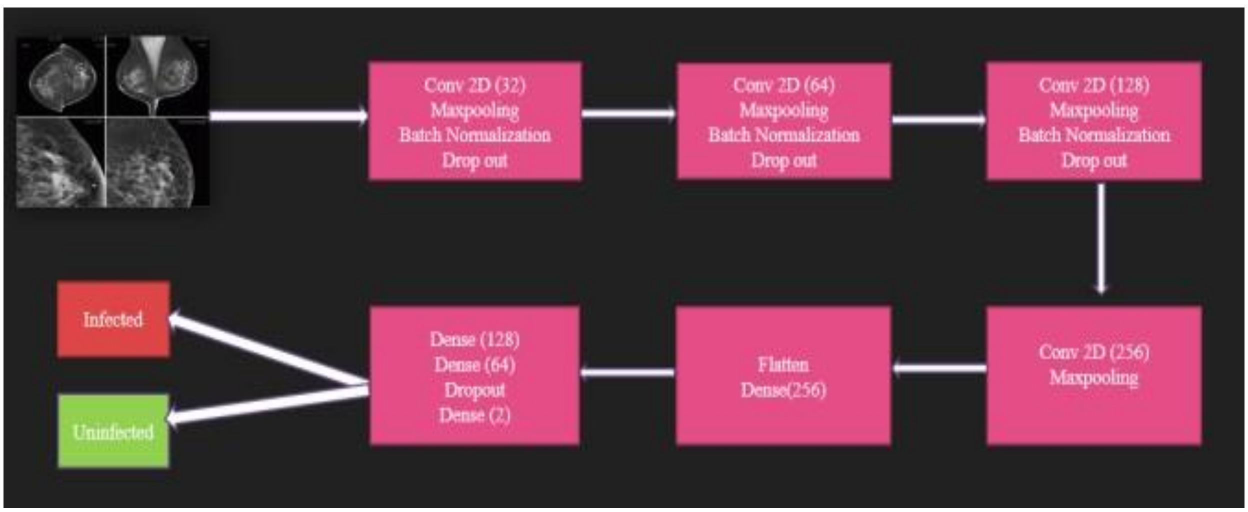

Figure 2: Proposed Architecture.

ModelTraining:

The model was trained on various data set on different disease such as malaria, retinopathy, brain tumor, breast cancer. The model was trained with followingparameters

1. Number of epochs-20
2. Batch Size –128
3. Validation split –0.3
4. Optimizer –'Adam'

5. Loss – Binary crossentropy
6. Metrics –accuracy.

ModelTesting:

The test image given and converted into numpy array. The input image should be resized according to the model input requirement on which it was trained.as the CNNmodel require 4D data and our input image is 3D data so input image should be reshaped to the 4D. once it is reshaped the image should be normalized by 255 and it has been converted into float 32. The image has been sent to the model for the prediction. Where the model tries to identify the features, which are related to infected or uninfected diseases.at last, we will get the percentage of the predicted label.

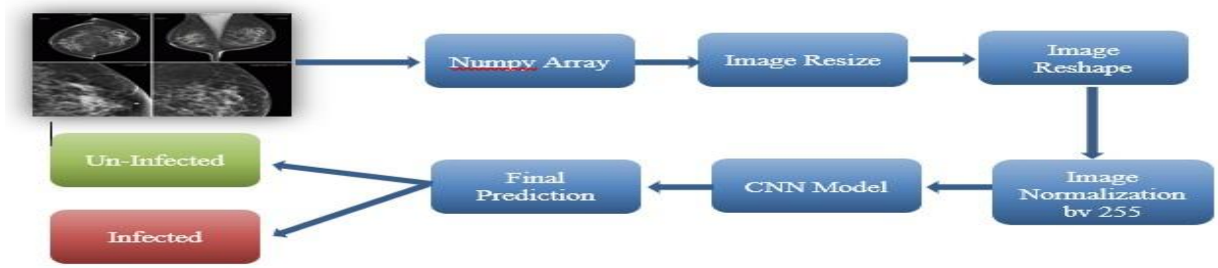

Figure 3: Model Testing

4. RESULTS

This section describes the experimental results of the proposed segmentation technique using Medical Images with different types of skin lesion . In the proposed method, the image data set is divided into two sets such as training set and testing set. The classifiers are trained with the training images and the classification accuracy is calculated only with the testing images. In the testing phase, the testing dataset is given to the proposed technique to find the cancer in Medicalimages and the obtained results are evaluated through evaluation metrics namely, sensitivity, specificity and accuracy[20].

$$Sensitivity = TP/(TP+FN)$$
$$Specificity = TN/(TN+FP)$$
$$Accuracy = (TN+TP)/(TN+TP+FN+FP) \qquad (15)$$

Where TP corresponds to True Positive, TN corresponds to True Negative, FP corresponds to False Positive and FN corresponds to False Negative. After training the model with two different approachesas described in section III. We have evaluated the model with different metrics parameters – Accuracy, Precision, and Recall, AUC-ROC curve, F1 score, Confusion matrix, individual emotions-based accuracy andreport

Architecture Proposed CNN	Data set			
	Malaria	Validation	Test	Cross Validation
Proposed CNN	Brain Tumor	**95.75%**	**95.54%**	**89.05%**
Proposed CNN	Retinopathy	**87.60%**	**87.21%**	**75.65%**
Proposed CNN+VGG 16	BreastCancer	**88.06%**	**88.13%**	**78.82%**
Proposed CNN	Pneumonia	**59.47%**	**59.47%**	**55.73%**

TABLE 1. Accuracy

Table 1 describes the Accuracies obtained for various models in which layers are varies accordingly.

For Malaria data set on proposed CNN was able to predict correctly 3999 as infected out of 4157 and predicted correctly 3905 as uninfected out of 4210 by giving training accuracy of 98.23% and test accuracy of 95.6%.

ForPneumoniadatasetonproposedCNNwasableto predict correctly 20488 as infected out of 22000 and predicted correctly 25810 as uninfected out of 27000 by giving training accuracy of 100% and test accuracy of 99.5%

For Retinopathy data set on proposed CNN was able to predict correctly 1918 as infected out of 2130 and predicted correctly 1650 as uninfected out of 1700 by giving training accuracy of 98.8% and test accuracy of 95.6%.

For Breast Cancer data set on proposed CNN was able to predict correctly 3999 as infected out of 4157 and predicted correctly 3905 as uninfected out of 4210 by giving training accuracy of 86.9% and test accuracy of 92.2%.

5. Comparative analysis:

In this section, the proposed method is compared to other three bench mark deep learning methods such as ResNet50, Xception, DenseNet121. Based on the experimental results our proposed work produces better results to other methods.

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ResNet50: Residual Networks (ResNet) is used as a backbone for many computer vision tasks as it comprises of 178-layer deep CNN architecture, consisting of convolutional, maxpool, batch normalization, activation and a dense layer. It allows us to train 150+ layers deep neural networks with ease. Before ResNet, training of deep neural networks was difficult due to the vanishing gradients. It involves the Add layer which allows us to form a skip connection i.e. output of predecessor layer that can be communicated as the input of successor layer [11].

Xception: Xception stands for "Extreme Inception" and consists of 36 convolutional layers for feature extraction along with pooling layers like maxpool and global average pool. These layers are structured in the form of 14 modules, where each convolutional layer consists of 3x3 filters and strides equal to 2. The convolutional layers are preceded by batch normalization. The relu activation function is followed throughout the architecture to bring out the non-linearity in the output of each layer. The exit of the architecture has a global average pool layer which is followed by a dense network and logistic regression [12-13].

DenseNet121: DenseNet121 consist of dense blocks which makes it different from other architectures. A dense block consists of subsequent layers which take features of the preceding layers as input via concatenation. Image is passed as input to the convolution layer which is followed by dense blocks each of them separated by a combination of convolutional of filter size 1x1 and 2x2 average pooling layer with a stride of 2 units. Each dense block consists of a combination of zero padding, convolution layer, batch normalization and activation layer. The block ends with a concatenation layer which concatenates the output of preceding layers. The tail of architecture consists of a dropout layer having a dropout rate of 0.2 followed by a dense layer of 1 unit and sigmoid activation [14-15]. The performance results of proposed and bench mark methods are given in Table 2. The Overall experimental results of existing and proposed methods are shown in Figure 4.

Table 2: Comparative analysis of other deep learning models and proposed method

Bench mark Methods	Sensitivity (%)	Specificity (%)	Accuracy (%)
Xception	96.79	98.92	98.40
CNN	94.18	97.86	96.80
ResNet50	92.24	98.07	97.13
DenseNet121	90.25	96.15	94.26
Proposed Architecture	97.51	98.78	98.43

(DCNN)			

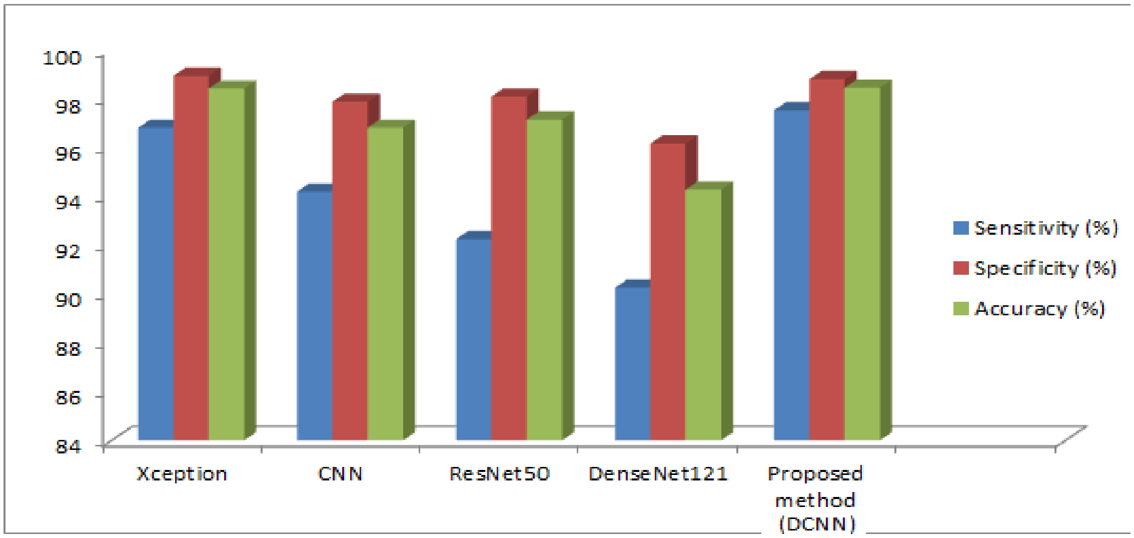

Figure 4 The Overall, experimental results of existing and proposed methods

5. CONCLUSION

During the recent few years, deep learning has gained a central position toward the automation of our daily lifeanddeliveredconsiderableimprovementsascomparedto traditional machine learning algorithms. Based on the tremendous performance, most researchers believe that within next 15 years, deep learning-based applications will take over human and most of the daily activities with be performed by autonomous machine. However, penetrationof deep learning in healthcare especially in medical image is quite slow as compare to the other real world problems. In thischapter,wehighlightedthebarriers thatarereducingthe growth in health sector. In last section, we highlighted state of the art applications of deep learning in medical image analysis. Though, the list is by no means complete however it provides an indication of the long-ranging deep learning impact in the medical imaging industry today. Finally, we have highlighted the open research issues.

Many big research organizations are working on deep learning based solution that encourage to use deep learning to apply deep learning on medical images. Looking to the brighter side of machine learning, we are hoping the sooner human will be replaced in most of the medical application especially diagnosis. However, we should not consider it as only solution as there are several challenges that reduces its growth. One of the big barriers is unavailability of annotated dataset. Thus, this question is still answerable, that whether we will be able to get enough training data without effecting the performance of deep learning algorithms. Recent development on other application showed that bigger the data, better the result, however, how big data could be used in healthcare.So far deep learning-based application provided positive feedback, however, but due to the sensitivity of healthcare data and challenges, we should look more sophisticated deep learning methods that can deal complex healthcare data efficiently. Lastly we conclude that there are unlimited opportunities to improve healthcare system

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