

Detection of cancerous tissue in histopathological images using Dual-Channel Residual Convolutional Neural Networks (DCRCNN)

Sabyasachi Chakraborty*, Satyabrata Aich*, Avinash Kumar**, Sobhangi Sarkar**, Jong-Seong Sim*,

Hee-Cheol Kim*

* Department of Computer Engineering/Institute of Digital Anti-Aging Healthcare/u-HARC, Inje University, South Korea

** School of Computer Engineering, KIIT University, Bhubaneswar, India

c.sabyasachi99@gmail.com, satyabrataaich@gmail.com, avinash1605@gmail.com, shobhangisarkar@gmail.com
jssin93@naver.com, heeki@inje.ac.kr

Corresponding Author: heeki@inje.ac.kr

Abstract— Computer-aided detection techniques to improve precision diagnostic capability and efficiency in the diagnosis process has been regarded as one of the most important topics in the field of computer vision. The medical imaging data with respect to a patient is primarily considered as one of the most important sources to derive the information regarding the biomarkers of a particular disease. But the successful detection of biomarkers requires the radiologist and the pathologist to have long term experience in this field. Therefore, the development of computer-aided detection is one of the primary concerns that need to be discussed. Moreover with the advent of Deep Learning and Artificial Intelligence, now the detection of anomalies and aneurysms in the medical imagery can become much more precise and efficient. Therefore this particular paper presents a dual-channel residual convolution neural network (CNN) model for the automated classification and detection of cancerous tissues in histopathological images. The proposed CNN model has been trained with 220,025 histopathological images and has achieved an overall accuracy of 96.475%, average recall of 95.72% and an average precision of 95.92% respectively.

Keywords— DCRCNN, CNN, Deep Learning, Histopathology, Cancer

I. INTRODUCTION

Cancer is a medical state which occurs due to abnormal growth of tissues in the body. It is found that all the organs except the heart are prone to cancer. Cancer leads to the dysfunction of crucial organs and various systems in the body. There are chances that cancer can spread and can target a new zone in the body. There are many types of cancer such as breast cancer, colon cancer, prostate cancer, skin cancer, etc. The number of cancer patients is increasing day by day. Cancer is a major threat to mortality and reduces life expectancy. There are many causes of cancer and some of them are pollutions, modern food, drugs and lack of exercise. The cancer detection is done by biopsy which is a very time extensive and invasive process and causes a lot of discomfort to patients. But with the emergence of smart technologies and precision healthcare, the detection of cancer is becoming easier. New modern techniques have been developed and are used in the detection of cancer. A

continuous evaluation related to cancer research has been performed. The accurate prediction of a disease outcome is one of the most interesting and challenging tasks as the computer-aided detection system became one of the most popular systems for medical researchers.

This technique can discover and identify patterns and relationships between features in histopathological images and can effectively predict the future outcomes of a cancer type. It is clear that the application of machine learning methods could improve the accuracy of cancer susceptibility, recurrence and survival prediction. Based on [1], the accuracy of cancer prediction outcomes has significantly improved by 15%–20% in the last years, with the application of ML techniques. Therefore in this paper, we propose a deep learning-based computer-aided cancer detection system by leveraging histopathological images.

The paper is organized as follows: The related work and recent studies that have motivated us to perform the work have been depicted in section II. The complete methodology, from data extraction to model development has been discussed in section III. Section 4 further presents the results followed by Section 5 which discusses the paper and lastly the paper is concluded in Section VI.

II. RELATED WORK

There has been a considerable amount of research that focuses on the problem of auto-detection and categorizing histopathology images of breast cancer and these research efforts have provided valuable findings regarding this problem. The general approach towards these kinds of problem is to train a classifier model which would classify the above-mentioned images into two-cancer and non-cancer or classify the cancer images into their different grades based of the features extracted from images.

So in the domain of cancer detection researchers focused more on using machine learning and deep learning algorithms. Turki [2] in his research performed a detailed study of the performance of machine learning algorithms for cancer detection. For his assessment, he used sample data of colon

cancer, liver cancer, and thyroid cancer. He applied machine learning algorithms such as AdaBoost, deep boost, XgBoost and support vector machines and on the basis of area under the curve and accuracy on actual clinical data, the author evaluated the above-mentioned algorithms. The author also performed the cross-validation method for checking the generalizability of the model. From the accuracy, the author concluded that support vector machines performed better than other algorithms. For using any machine learning algorithm proper analysis of images needs to be done. Veta et al.[3] in his research has presented valuable insights for researchers who have begun to research in this domain. In this paper they have explained all the primary steps that are performed at the beginning of analysis of cancer images, it explains how the tissues are prepared, staining process is done and slides are digitized followed by discussion on several image analysis technique like clustering or classification of RGB pixels to obtain the probability of occurrence for various stains or color standardization based on division of different tissue components. Further, these tissue components have been identified by classifying each small rectangular box using supervised classification algorithms.

So, from image analysis, we can find out different low levels and high-level features that can be used to classify the image but Fischer et al. [4] in his research did a detailed assessment of the relation of breast cancer with the age of the patient. For this purpose, he collected the data of around 1869 women who were suffering from breast cancer and were treated at Guy's Hospital. The patients were grouped according to their ages. Four groups of age group <39 years, 40-49 years, 50-69 years and 70 years were made. The chi-squared test was used to calculate the statistical differences that prevailed among different age groups. Logistic regression was further used to predict different samples of different subgroups. On the basis of the study, the author concluded that tumor types and mainly lobular are frequent in women of the oldest age group. Moradi et al. [5] in his research focused on the study of different kinds of image-based techniques for the detection of prostate cancer and its grade. The author particularly used images of ultrasound, MRI and histopathology images but among all these images the author preferred using ultrasound images for cancer detection. For feature extraction, the study used ultrasound echo, RF signals, generated b-scan images and doppler images to classify the prostate. The focus was mainly on how well ultrasound images perform for cancer detection with techniques like RF spectrum features with nonlinear classification.

Moreover, with the advent of deep learning a lot of study has been performed with respect to the detection, classification, and segmentation of cancerous tissue from histopathological images. Alom et al. [6], developed an Inception Residual Convolutional Neural Network (IRRCNN) model for the classification of Breast Cancer from histopathological images. The novelty of such a model was that it was developed on the basis of three powerful deep Learning architectures namely, Inception network, Residual Network, and Recurrent Networks. The results of the IRRCNN model were further

compared with the results of state-of-the-art models, moreover, a testing accuracy of 99.05% was obtained.

In a similar manner, for a different dataset with 24 different categories of histopathological images, Talo [7] performed a study. The study leveraged the usage of DenseNet-161 and ResNet-50 on 23,916 whole slide images of dimensions 1000px X 1000px. The DenseNet-161 and ResNet-50 models performed astoundingly by propelling an accuracy of 97.89% and 98.87% respectively. Another very interesting study was discussed by Wang et al. [8] where a novel bilinear CNN (BCNN) was developed for the classification of histopathological images of colorectal cancer into 8 different classes. The study was performed on 1000 non-overlapping images of 150 X 150 pixels. The BCNN model performed better than the state-of-the-art CNN models by prompting an accuracy, sensitivity, and specificity of 92.6%, 92.8%, and 98.9% respectively.

III. METHODOLOGY

A. Data Collection and Specification

The data for the project has been collected from the Kaggle data repository [9]. The complete data set contains 220,025 histopathological images. The histopathological image patches that were obtained were of size 96px width and 96px height. The images primarily belonged to two different classes namely, Positive and Negative. The images belonging to the positive classes had a single tumor cell present in the complete image and the images belonging to the negative classes had no tumor cell. Figure 1 plotted below shows the sample images that were obtained for both the classes, where Class 0 shows the histopathological images with no tumor cell presence and Class 1 shows the histopathological images with the presence of tumor cells.

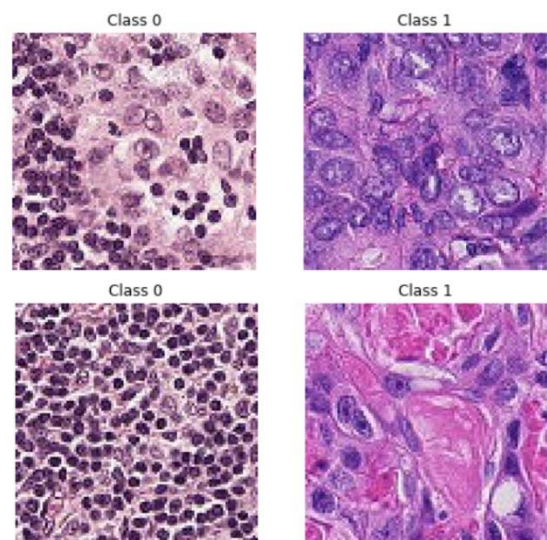


Figure 1. Sample Images for both the classes

B. Data Pre-processing and Augmentation

The images used in the study were subjected to a stain decomposition algorithm developed by [10]. The algorithm developed was specifically used for the separation and quantification of immunohistochemical staining using color image analysis. Figure 1 depicted below shows two sets of images i.e. (i) without the presence of tumor tissue and (ii) with tumor tissue. Both the set of images have been processed with the stain decomposition algorithm to separate the Hematoxylin component and the Eosin component.

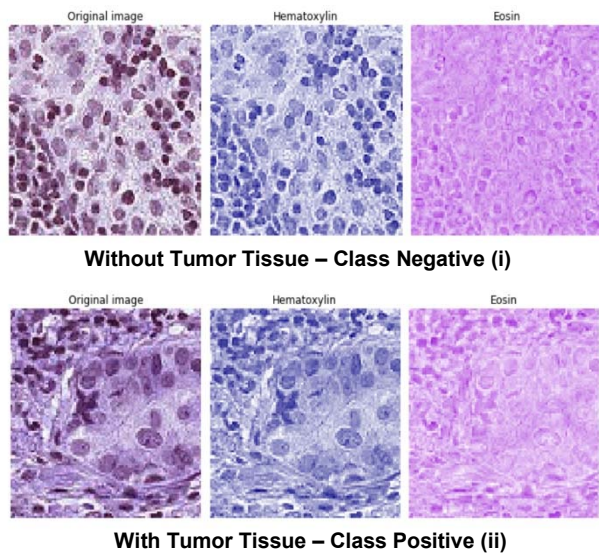


Figure 2. Stain decomposition of Histopathological images for both the classes.

Further in the study, as the primary motive is regarding the development of a CNN model, therefore a static policy-based augmentation was performed. The augmentation in the training data necessarily helps to increase the diversity in the dataset for the training. Therefore the image augmentations were performed only on the training data. Table 1 below shows the parameters that were selected for the purpose of data augmentation. Also, Figure 3 below shows the sample of images that were used for the training purpose and have undergone augmentation.

TABLE 1. DATA AUGMENTATION PARAMETERS

Augmentation Parameters	Settings
Horizontal Flip	True
Vertical Flip	True
Random Brightness	True
Random Contrast	True
Random Saturation	True
Random Hue	True
Minimum Crop Percentage	0.1
Max Crop Percentage	0.5
Crop Probability	0.3
Rotation Range	30

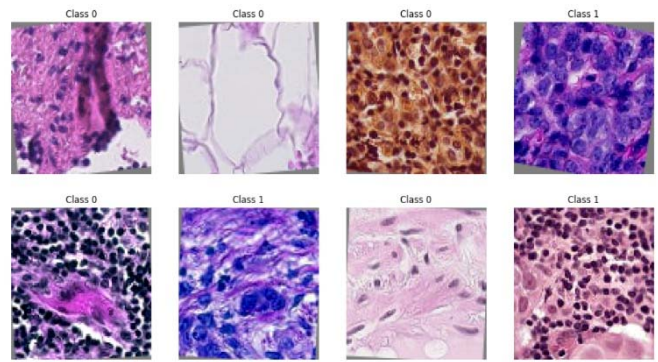


Figure 3. Augmented Images for Training

C. Model Development

Recent developments in the field of machine intelligence have created a mighty paradigm shift to solve some of the most precise and difficult problems. But mostly, after the emergence of deep learning and more specifically convolutional neural networks the world of computer-aided detection systems have seen massive disruptions, where the automated systems are able to plot much more accurate and precise results efficiently. Moreover, the histopathological images that are often used by physicians and doctors for diagnosing a multitude of health issues are considered as the primary biomarker when it comes to early-stage cancer detection. But the process of evaluating such a massive number of histopathological images increases a huge overhead on the pathologists and also, the diagnosis of such images needs a tremendous amount of expertise and patience on the part of the pathologists.

Therefore, in this study, we have developed a deep learning model for the classification of histopathological images with respect to the detection of cancerous tissue in whole slide images. For the classification of the histopathological images, a Dual-Channel Residual Convolutional Neural Network (DCRCNN) model was developed as shown in Figure 4. The dual-channel in the name suggests that the deep learning architecture developed has two input channels. The two channels in the architecture correspond to the two different types of stains in histopathology images namely, Hematoxylin and Eosin. All 220,025 images were decomposed into two different sets of images namely, hematoxylin and eosin set respectively.

In Figure 4, which represents the DCRCNN architecture is primarily divided into three different sections. The first section is the input section where the input of two different networks is initialized and the images based on Hematoxylin and Eosin stains are passed respectively. Section 2 describes the ResNet50 architecture of both the input channels which are responsible for creating the feature representations of the histopathological images. The final section that is Section 3, concatenates the feature representation created by the final convolution layer. Further the concatenated feature representation is passed through a global average pooling layer and finally, the outputs

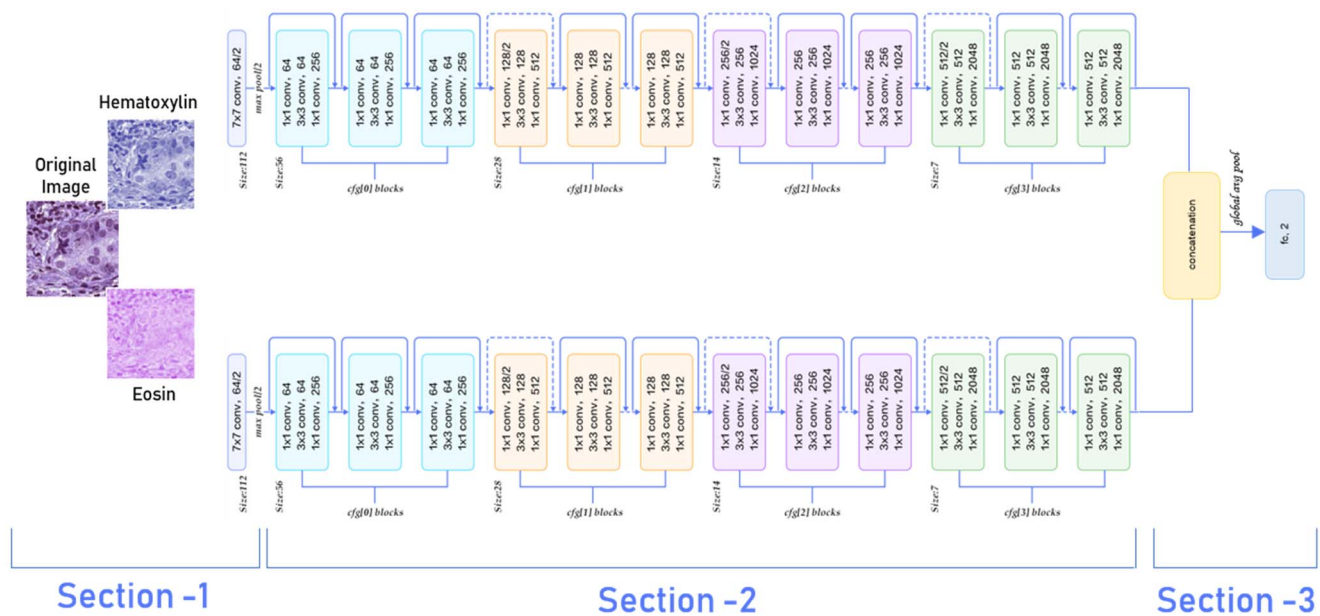


Figure 4 . Dual Channel Residual Convolutional Neural Network Architecture

of the global pooling layer are connected to a fully connected layer of 2 Neurons which resembles the probability values for two classes based on the Sigmoid activation function.

D. Model Optimization and Hyperparameter Tuning

The DCRCNN model that has been developed in the work leveraged Adam (Adaptive Moment Estimation) [13] optimizer for the optimization of the cost function that is the binary cross-entropy. For the tuning of hyperparameters of the optimizer algorithm Adam, Bayesian Sequential Model Optimization was performed. Bayesian SMBO is a hyperparameter optimization that minimizes a particular objective function by developing a surrogate model based on the previous evaluation results of the objective function.

The set of hyperparameters that were chosen for the optimizer function were as follows, learning rate: 0.8, beta-1: 0.9468841, beta-2: 0.74896 and decay: 0.000569. Moreover, for the learning rate, a certain policy was defined where whenever for 3 consecutive epochs if the validation loss doesn't decrease then the learning rate must be reduced by the fraction of 0.6.

IV. RESULTS

The DCRCNN model that was developed in the study provided us with some sound results on the predictive power of the classification of histopathologic images containing tumor cells and not containing tumor cells. The model developed prompted an accuracy of 96.475%, recall of 96.72%, precision of 95.92% and f1 score of 96.32%. Moreover, a 5 Fold cross-validation was also performed on the complete dataset to check the generalizability of the model and it was found that the

model generalized pretty decently over the two classes and also showed a constant tendency towards the precision and recall over random data folds of training, validation, and testing. The dataset for the testing of the model contained 22,003 histopathological images from both the classes. Figure 5 shown below depicts the confusion matrix of the model. In the figure, it can be seen that there are a few mispredictions that have taken place. Upon controlled examination of the mispredictions, it was found out that the images that were mispredicted had some abnormalities or had some kind of inertial noise which resulted in a poor predictive power for those specific images.

		Predicted Label	
		0	1
True Label	0	10156	344
	1	432	11071

Figure 5. Confusion Matrix

Moreover, Figure 6 (a) and (b) depicted below shows the performance graph of the model. The performance graph shows that the model ran for 50 epochs whereas while fitting the model a maximum limit of the running of the epoch was kept to be 1000 while accompanying an early stop protocol. The early stop protocol was devised in such a way that, if the validation loss does not decrease for consecutive 6 epochs and

also by reducing the learning rate twice by the fraction of 0.6 then the model needs to be stopped.

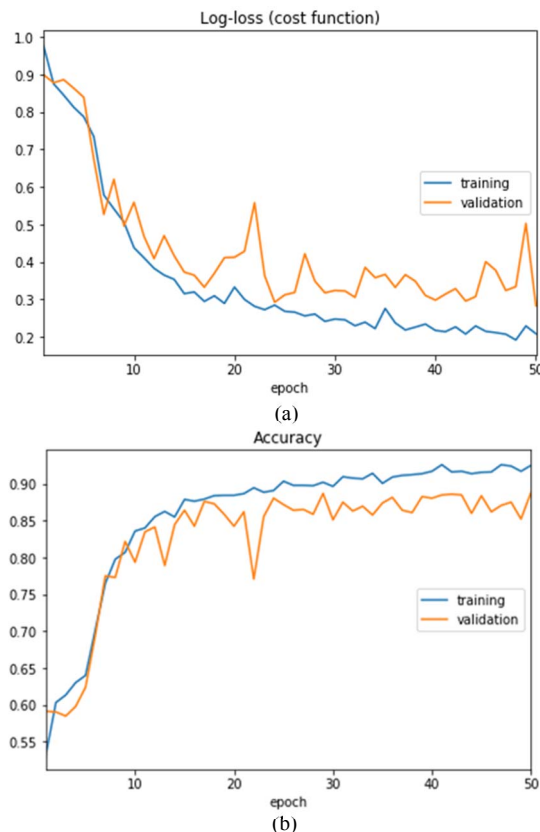


Figure 5. Performance Graph

V. DISCUSSION

The DCRCNN model developed in the work pursues some astounding results on classifying histopathological images containing cancerous cells. Such kind of classification models are very much necessary in the computer-aided detection systems in the real world as with the increase in the number of diagnostic samples there is not enough amount pathologist or physicians who can carefully mutate upon the whole slide images for the identification of unwanted growth in the cells. Therefore presently there is a vital need for automating such detection procedures as these kinds of systems can possess a weighted value with respect to the decision made by the pathologists.

The work predominantly used a stain decomposition method for separating the Hematoxylin component and the Eosin component from the histopathological images. The stain decomposition that is used in the work primarily helps to identify the cellular components. After stain decomposition is applied to the histopathological images, both the stains are further subjected to a DCRCNN model where each channel takes a particular type of stain as input and further allows a ResNet model to train upon the stained images. In the later part, the feature representation created by both the ResNet50 models is concatenated to create a single feature representation that is further subjected to a fully connected layer for the classifying the images into the two classes.

VI. CONCLUSION

In this paper, a DCRCNN model was developed for the classification of histopathological images that contained cancerous cells from the normal histopathological images. The work predominantly leveraged the stain decomposition method for separating the Hematoxylin component and the Eosin component from the histopathological images. DCRCNN model that has been developed in the work plotted some astounding results by prompting an overall accuracy of 96.475%.

The methodology provided in the paper can be further improved by using some different set of features at the input section and also by iterating over other states of the art CNN architectures in the second section. But the present system enabled us with much confidence that this kind of system can be employed in real-life scenarios and stable production environments.

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Sabyasachi Chakraborty is pursuing his Master's in computer engineering from Inje University. He has previously worked on multiple real-life projects related to computer vision, data sciences, biosignal analysis and text mining. His research interest aligns with Computer Vision, Artificial Intelligence, BioSignal Processing, Algorithms, and Blockchain.



Satyabrata Aich is working as a research professor in the field of computer engineering. He has published many research papers in journals and conferences in the realms of Machine learning, Text mining, and Supply Chain Management. His research interests are natural language processing, Machine learning, supply chain management, Bioinformatics, Artificial Intelligence, Blockchain.



Avinash Kumar is a Final year student. He is pursuing B.Tech in Computer Science and System Engineering from KIIT, Deemed to be University, Bhubaneswar, India. His research interests area includes Image Processing, Deep Learning and Machine Learning.



Sobhangi Sarkar is a Final year student. She is pursuing B.Tech in Computer Science and Communication Engineering from KIIT, Deemed to be University, Bhubaneswar, India. Her research interests area includes Deep Learning, Image Processing and Machine Learning.



Sim Jong Seong is a graduate student of the Institute of Digital Anti-aging and Healthcare. He has completed his BS degree in the department of computer engineering, Inje University. His research interests are system design and development, framework development, cloud computing, Blockchain architecture development



Hee-Cheol Kim received his BSc at the Department of Mathematics, MSc at the Department of Computer Science in SoGang University in Korea, and Ph.D. at Numerical Analysis and Computing Science, Stockholm University in Sweden in 2001. He is a Professor at the Department of Computer Engineering and Head of the Institute. Digital Anti-aging Healthcare, Inje University in Korea. His research interests include Machine learning, Text mining, Bio Informatics.