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Organised by
Department of
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Convenors:
Dr.B.Sundarambal
Dr.R.Janarthanan

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PREFACE

The 21st century has witnessed a paradigm shift in three major disciplines of knowledge i. Computing, ii. Communication and iii. Information Technology. While first two are complete in themselves by their titles, the last one covers several sub-areas involving bio, geo, medical and cognitive informatics among many others. Actually, the above three major areas of knowledge 4.0 are complementary and mutually exclusive but their convergence is observed in many real world applications, encircling cyber security, Database technology, Data Science, Machine learning, deep learning, AI, Internet banking, health care, network security, AR/VR, industry 4.0, Internet of Things (IoT), sensor network, web technology, cognitive learning, data mining, mobile computing, grid computing, cloud technologies, green computing, quantum computing and many others.

The international conference on Computing, Communication and Information Technology (I3CIT 2020) is aimed at investigative the meeting of the above three modern areas through interaction among three groups of people. I3CIT 2020 (International Conference on Computing Communication & Information Technology) is an International Conference in the area of Computing, Communication and Information Technology focusing to address the issues and developments in Science, Engineering and Technology.

The aim of this conference is to put emphasis on the need for emerging technology in computing communication and information technology. It also provides a forum for National /international Research Scholars, software industry people and Professionals, consultants, Faculty, PG and UG Students to discuss and evolve solutions for various difficulties faced during developments. The conference serves as a forum to foster the exchange of experiences among researchers, improve research quality and address current issues.

Upon successful completion of this conference, the participants will be able to gain insight on Advanced Computing, Communication & IT and Techniques in Computer Science & Engineering thereby promoting Sustainable development. The benefits of this conference are more towards the potential use of information technology in computer science and engineering.

All the keynote speakers and invited papers were reviewed by the Review Committee and grouped under two technical sessions. It has been so designed that the conference will launch off with address from the invited **Chief Guest** ***Padma Shri. Dr. Mylswamy Annadurai,*** *Former Director of ISRO and Vice President of TNSCST, Chennai, Tamil Nadu.*followed by keynote addresses from the invited guests *Special Guest* ***Dr. E. K. T. Sivakumar,*** Visiting Professor, Centre for Nanoscience and Technology, Anna University, Chennai-600 025. Tamil Nadu, India and **Mrs. G. Geetha**, Informatica LLC, Vice President, Global Customer Support, California, USA and the presentations by the participants from various Institutions. The editorial committee has also formed to publish proceedings of the International Conference.

We take this Opportunity to thank our **Chairman Shri. P. Sriram, Vice Chairman Shri. P. Janakiraman** and **Secretary Mrs. S. Sridevi** for giving us all support and encouragement to make this Conference a grand success. We also express our sincere thanks to our **Principal Dr. P. Partheeban** for extending the support to conduct the conference in successful manner.

We would like to mention the untiring efforts put forth by the **Teaching and Non-teaching staff and the students of the Department of Computer Science and Engineering & Information Technology** and thank them profusely.

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Deep Convolutional Neural Networks for Early Detection of Breast Cancer

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ABSTRACT

In this paper we developed a Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNNs) that aims to help the radiologist classify mammography mass lesions. Deep learning usually requires large datasets to train networks of a certain depth from scratch. Transfer learning is an effective method to deal with relatively small datasets as in the case of medical images, although it can be tricky as we can easily start over fitting. In this work, we explore the importance of transfer learning and we experimentally determine the best fine-tuning strategy to adopt when training a CNNs model. We were able to successfully fine-tune some of the recent, most powerful CNNs and achieved better results compared to other state-of-the-art methods which classified the same public datasets. Furthermore, after pre-processing and normalizing all the extracted Regions of Interest (ROIs) from the full mammograms, we have to merge all the datasets to build one large set of images and used it to fine-tune our CNNs.

Keywords: Mammogram, Neural Network, Enhancement, CLAHE, MSE, PSNR

I. INTRODUCTION

Breast cancer is one of the most common invasive diseases among women worldwide. In 2016, there were more than 2.8 million women with a history of breast cancer in the U.S and this includes women currently being treated and women who have finished treatment. In 2017, 1,688,780 new cases of breast cancer are expected to be diagnosed and 600,920 cancer deaths are projected to occur, though death rates have been decreasing since 1989[1]. These decreases are thought to be the result of treatment advances, increased awareness and earlier detection through screening. Mammography is the recommended imaging modality for breast cancer screening; it is more useful as an early detection tool before the appearance of the physical symptoms. Early Diagnosis of the disease via mammography screening increases the chances of recovery dramatically.

Computer-aided Diagnosis (CAD) systems aim at giving a second objective opinion to assist the radiologist medical images interpretation and diagnosis. CAD systems are especially used as applications that perform the labeling or differentiation between benign and malignant lesions. The deep learning CAD's were introduced to different medical domains. Most of the proposed methods involved CNNs but in a traditional way, where they use only the extracted CNN features or combine them with some other hand-crafted descriptors to carry out the classification task. Convolution Neural Networks learn discriminative features automatically, their architecture is particularly adapted to take advantage of the 2D structure of the input image, but more importantly one of their most impressive characteristic is that they generalize surprisingly well to other recognition tasks. In order to train deep CNNs we need large annotated datasets which are lacking in the medical domain especially for breast cancer[2]. Moreover, training a CNN from scratch requires high computational power, large memory resources and time, and with the little data provided we can easily start over fitting. One way to overcome this is to use transfer learning from natural images.

Transfer learning is commonly used in deep learning applications. It has been very effective in the medical domain. When the amount of data is normally limited, using transfer learning from natural images to breast cancer mammography images, has not yet been fully explored in the literature. And, as far as we know the only work .which uses transfer learning to classify breast lesions, employs small sized datasets and the deep Convolution Neural Network CNN-F as a model.

II. LITERATURE SURVEY

This section reviews the previous published literatures, books and documents which lay the foundation and basis for further work in this project. This helps to give a better understanding about the topic and also acts as a guideline for this thesis.

The paper entitled "Deep Convolutional Neural Networks for breast cancer screening"[1] by Hiba Chougrad , Hamid Zouaki , Omar Alheyane , In this paper we developed a Computer-aided Diagnosis (CAD) system based on deep Convolutional Neural Networks (CNNs) that aims to help the radiologist classify mammography mass lesions. Deep learning usually requires large datasets to train networks of a certain depth from scratch. Transfer learning is an effective method to deal with relatively small datasets as in the case of medical images, although it can be tricky as we can easily start over fitting.

The paper entitled "Feature Extraction from Histopathological Images Based on Nucleus-Guided Convolutional Neural Network for Breast Lesion Classification" [2] by Yushan Zheng, Zhiguo Jiang, Fengying Xie, Haopeng Zhang, Yibing Ma, Huaqiang Shi, Yu Zhao, In this paper we Feature extraction is a crucial and challenging aspect in the computer-aided diagnosis of breast cancer with histopathological images. In recent years, many machine learning methods have been introduced to extract features from histopathological images. In this study, a novel nucleus-guided feature extraction framework based on convolutional neural network is proposed for histopathological images. The nuclei arrest detected from images, and then used to train a designed convolutional neural network with three hierarchy structures.

The paper entitled "Computer-aided diagnosis of mammographic masses based on a supervised content-based image retrieval approach" [3] by Lazaros Tsochatzidis, Konstantinos Zagoris, Nikolaos Arikidis, Anna Karahalion, Lena Costaridou, Ioannis Pratikakis. In this paper we the incorporation of content-based image retrieval (CBIR) into computer aided diagnosis (CADx) is investigated, in order to contribute to the decision-making process of radiologists in the characterization of mammographic masses. The proposed scheme comprises two stages: A margin-specific supervised CBIR stage that retrieves images from reference cases along with a decision stage that is based on the retrieved items. The feature set utilized exploits state-of-the-art features along with a newly pro- posed texture descriptor, namely mHOG, targeted to capturing margin and core specific mass properties.

The paper entitled “Large scale deep learning for computer aided detection of mammographic lesions” [4] by Thijs Kooi, Geert Litjens, Bram van Ginneken, Albert Gubern-Mérida, Clara I. Sánchez , Ritse Mann, Ard den Heeten , Nico Karssemeijer . In this paper we recent advances in machine learning yielded new techniques to train deep neural networks, which re- sulted in highly successful applications in many pattern recognition tasks such as object detection and speech recognition. In this paper we provide a head-to-head comparison between a state-of-the art in mammography CAD system, relying on a manually designed feature set and a Convolutional Neural Network (CNN), aiming for a system that can ultimately read mammograms independently. Both systems are trained on a large data set of around 45000 images and results show the CNN outperforms the traditional CAD system at low sensitivity and performs comparable at high sensitivity.

The paper entitled “Breast Cancer Diagnosis in DCE-MRI using Mixture Ensemble of Convolutional Neural Networks” [5] by Reza Rastia, Mohammad Teshnehlab, Son Lam Phung In this paper we This work addresses a novel computer-aided diagnosis (CAD) system in breast dynamic contrast enhanced magnetic resonance imaging (DCE-MRI). The CAD system is designed based on a mixture ensemble of convolutional neural networks (ME-CNN) to discriminate between benign and malignant breast tumors. The ME-CNN is a modular and image-based ensemble, which can stochastically partition the high-dimensional image space through simultaneous and competitive learning of its modules. The proposed system was assessed on our database of 112 DCE-MRI studies including solid breast masses, using a wide range of classification measures.

The paper entitled “Deep learning-based assessment of tumor-associated stroma for diagnosing breast cancer in histopathology images” [6] by Babak Ehteshami Bejnordi, Jimmy Linz, Ben Glass, Maeve Mullooly, Gretchen L Gierach, Mark E Sherman, Nico Karssemeijer, Jeroen van der Laak, Andrew H Beck. In this paper we diagnosis of breast carcinomas has so far been limited to the morphological interpretation of epithelial cells and the assessment of epithelial tissue architecture. Consequently, most of the automated systems have focused on characterizing the epithelial regions of the breast to detect cancer. In this paper, we propose a system for classification of hematoxylin and eosin (H&E) stained breast specimens based on convolutional neural networks that primarily targets the assessment of tumor associated stoma to diagnose breast cancer patients.

The paper entitled “Two-phase deep convolutional neural network for reducing class skewness in histopathological images based breast cancer detection” [7] by Noorul Wahab, Asifullah Khan, Yeon Soo Lee. In this paper Different types of breast cancer are effecting lives of women across the world. Common types include Ductal carcinoma in situ (DCIS), Invasive ductal carcinoma (IDC), Tubular carcinoma, Medullary carcinoma, and Invasive lobular carcinoma (ILC). While detecting cancer, one important factor is mitotic count showing how rapidly the cells are dividing. But the class imbalance problem, due to the small number of mitotic nuclei in comparison to the overwhelming number of non-mitotic nuclei, acts the performance of classification models.

The paper entitled "Improving Computer-aided Detection using Convolutional Neural Networks and Random View Aggregation" [8] by Holger R. Roth, Le Lu, Senior Member, IEEE, Jiamin Liu, Jianhua Yao, Ari Seff, Kevin Cherry, Lauren Kim, and Ronald M. Summers. In this paper automated computer-aided detection (CADe) in medical imaging has been an important tool in clinical practice and research. State-of-the-art methods often show high sensitivities but at the cost of high false-positives (FP) per patient rates. We design a two-tiered coarse-to-fine cascade framework that first operates a candidate generation system at sensitivities of 100% but at high FP levels. By leveraging existing CAD systems, coordinates of regions or volumes of interest (ROI or VOI) for lesion candidates are generated in this step and function as input for a second tier, which is our focus in this study. In this second stage, we generate N 2D (two-dimensional) or 2.5D views via sampling through scale transformations, random translations and rotations with respect to each ROI's centered coordinates.

III. METHODOLOGY

3.1 Pre-processing:

In order to enhance the performance of a CAD system, pre- processing is a mandatory step when building the dataset. In our work, we extracted the lesions as fixed sized ROIs then we normalized them using global contrast normalization. It illustrates the pre-processing steps for extracting and normalizing the ROIs.

ROI extraction: We used the ground-truth provided with each dataset to detect and crop the regions of interest (ROIs) from the images. The location and boundaries of the lesions were marked by imaging specialists. We used the provided coordinates to target and crop the bounding box of the lesions automatically. We fixed the input size ROIs to r x r pixels. We then rescaled the output image, for when the lesion is near the edges and the width or height of the cropped ROI is smaller than r.

Global contrast normalization (GCN): Normalization, also called zero-centering is a standard step in medical image classification. It attempts to deal with external sources of data variation like illumination levels, the different scanners used in the digitalization process and how this can affect the pixel values. Global contrast normalization computes the mean of intensities for each image, and then subtracts it from each pixel of the image.

Data augmentation: Deep learning models perform better when we have large datasets. One very popular way to make our datasets bigger is data augmentation or jittering. Data augmentation can increase the size of the dataset to 10 times the original one or more, which helps prevent over fitting when training on very little data. The approach helps build simpler and robust models which can generalize better.

3.2 Deep Convolutional Neural Networks models:

VGG16: There are several versions to the very deep Convolutional network (VGG) published by researchers from Oxford University, VGG16 is one of their best networks and is well known for its simplicity. The architecture of this network is deep and simple, it mainly consists of an alternation between convolution layers and dropout layers. VGG was the first to use multiple small 3×3 filters in each Convolutional layer and combine them in a sequence to emulate the effect of larger receptive fields. Although the network is simple in its architecture, it is very expensive in terms of memory and computational cost since the exponentially increasing kernels lead to higher computational time and a bigger size model. The implemented VGG16 architecture is composed of 13 convolutional layers, 5 pooling layers and achieves 9.9% top-5 error on ImageNet.

ResNet50: The ResNet50 is one of the models proposed in the deep residual learning for image recognition by the Microsoft research team .The authors came up with a simple and elegant idea. They take a standard deep CNN and add shortcut connections that bypass few convolutional layers at a time. The shortcut connections create residual blocks, where the output of the convolutional layers is added to the block’s input tensor. The ResNet50 model used has one convolutional layer followed by a batch normalization layer, and has two pooling layers in between which there is a total of 16 residual modules. Two kinds of residual modules are alternated, one that has 4 convolutional layers and another with 3 Convolutional layers.

Inception v3: The Google research team with Christian Szegedy was mainly focused on reducing the computational burden of CNNs while maintaining the same level of performance. They introduced a new module named “The inception module" which, for the most part, can be described as a 4 parallel pathways of 1 ×1, 3 ×3 and 5 ×5 convolution filters. And because of the parallel net- work implementation, in addition to the down sampling layers in each block, the model’s execution time beats VGG or ResNet. The Inception v3 we implemented has 5 convolutional layers each one followed by a batch normalization layer, 2 pooling layers and 11 inception modules. The inception modules used contain different numbers of paths and convolution layers. Authors of the Inception v3 did not define an “Inception cell" and then repeatedly applied it to downscale the input. Therefore, the inception modules used, sometimes consist of 4, 6, 7, 9 or 10 Convolutional layers followed by batch normalization and one pooling layer. The implemented model by Chollet achieves 7.8% as a top-5 error on ImageNet, same as ResNet50.

3.3 Transfer learning and fine-tuning:

As we begin to explore deep learning models from more specialized domains as the quantity of available data gets scarce. Even though we have impressive training methods nowadays, training deep learning models on small quantities of data is very difficult. The actual paradigm used to deal with this issue has come through the use of pre-trained neural networks.

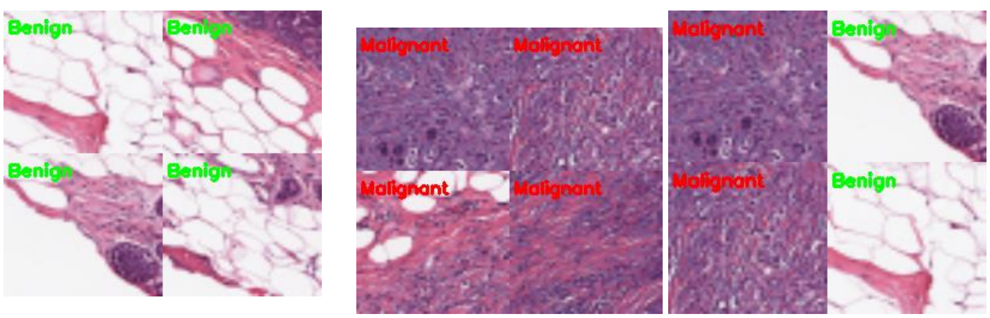
The first Convolutional layers of a CNN learn generic features and can perform more like edge detectors, which should be useful to many tasks, but the following layers become progressively more specific to the details of the classes contained in the dataset. In accordance with this statement and since mammographic mass lesion images are very different from ImageNet images, we propose to fine-tune our models to adjust the features of the last Convolutional blocks and make them more data-specific; we fine- tune the weights of the pre-trained networks using the new set of images by resuming the back propagation on the unfrozen layers.

We propose to investigate the adequacy of this technique for our case of study, either to deal with our little data or as a way for initializing the models. The CNN models are built differently but the same procedure is applied to all of them:

- For starters we kept the original networks architectures up till the fully-connected layers.
- The original fully-connected layers were built for the ImageNet dataset with 1000 outputs for 1000 class categories. We re- moved these last fully-connected layers and built our own fully- connected model, on top of the convolutional part of the models, suited to our number of classes (i.e. 2 classes "Benign" and "Malignant").

IV. SIMULATION RESULTS

The developed framework could predict and provide the correct diagnosis for 6244 images from IDC dataset, to get accuracy of 84.79%, Sensitivity 88.29% and Specificity 75.93% after doing 10 iterations. The results obtained from the receiver operating characteristic (ROC) curve analysis showed a high true-positive rate for all previous datasets, which means a high probability of correctly identifying malignant mass lesions as being cancerous.



a)Benign Cells **b) Malignant Cells** **c) Malignant & Benign Cells**

V. CONCLUSION

We can conclude that integrating the recent well-engineered deep learning CNNs through transfer learning into the screening mechanism brings an apparent improvement compared to other approaches. The fine-tuning strategy proposed improves the state-of-the-art accuracy classification on many public datasets. The Inception v3 model trained on the merged dataset, which achieved the best accuracy rate overall, was used to develop a mass lesion classification tool. The *Breast Cancer Screening Frame-work* devised, could successfully classify many "never-seen" images of mammography mass lesions. It provided highly accurate diag-noses when distinguishing benign from malignant lesions. There-fore, its output could be used as a "second opinion" to assist the radiologist in giving more accurate diagnoses.

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