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Cancer Detection from Medical Images using Deep Convolution Neural Networks

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Abstract: Cancer is a common disease that has caused fatalities among all age groups worldwide causing thousands of deaths each year. It is, therefore, necessary to diagnose cancer at an early stage. Deep learning has been proven pivotal for the early detection of cancer. This project uses deep convolutional neural networks to classify cancer in medical images belonging to four common cancers. This project is an effort to apply deep learning for cancer detection using both custom made DCNN models and pre-trained models. Images are analyzed using various edge detection algorithms. Data augmentation has been employed on the images. The four cancers image datasets used for this project are breast cancer histopathological images, brain MRI images, lungs CT scan images and skin lesion images. The performance of the proposed models is compared based on classification accuracy, precision, recall and f-score. After a comparison of the performances of the model, the model with the best performance will be deployed using flask REST API. This is an attempt to make the use of deep learning practical for a medical professional to diagnose cancer. This project is an attempt to bolster the previous research and development in the field of cancer diagnosis using deep learning.

Keywords: BrecanNet, BrainNet, Classification Accuracy, Deep Convolution Neural Network, LungNet, MelNet

I. INTRODUCTION

Cancer is a fatal illness often caused by genetic disorder aggregation and a variety of pathological changes. Cancerous cells are abnormal areas often growing in any part of the human body that is life-threatening. This ordered mechanism can occasionally fail, causing abnormal or damaged cells to develop and proliferate when they shouldn't. These cells can develop into tumors, which are tissue lumps. Tumors can be benign or cancerous (benign). Cancerous tumors can infect surrounding tissues and spread to other areas of the body, causing new tumors to develop (a process called metastasis). Cancerous tumors are also known as malignant tumors. Many cancers, including leukemia, produce solid tumors, whereas blood cancers do not. Cancer must be quickly and correctly detected in the initial stage to identify what might be beneficial for its cure. Even though modality has different considerations, such as complicated history, improper diagnostics and treatment that are the main causes of deaths. The cancer death rate (cancer mortality) is 158.3 per 100,000 men and women per year (based on 2013–2017 deaths)[1].

It is imperative to detect the possibility of cancer well in advance to decrease the fatalities caused by cancer. Recent years have seen an intense improvement in survival rates for ladies with cancer, which may be mainly attributed to an in-depth screening and enhanced treatment.

This project will predict four common types of cancer using various types of medical images. These include breast cancer, lung cancer, brain tumor and skin cancer using histopathological images, CT scan images, MRI images and common skin images respectively. Data augmentation on the images has been applied to modify and generate synthetic data on the small datasets. Custom models using Convolution Neural Network(CNN) have been designed for each cancer using Keras Sequential API. Two pre-trained models have also been trained on the images using transfer learning. The need to apply data augmentation is to regularize and reduce overfitting in the training of the models.

The training results of the model are evaluated on classification accuracy, precision, recall, f-score and ROC values. One complicating factor is that the image datasets are unbalanced in nature with the majority of the images belonging to one particular class. The use of classification accuracy alone for the evaluation is not enough. Sensitivity and specificity have to be used as well for the evaluation of model performances. A comparative study of the performance results of the above-mentioned models has been done. The model has the best performance on the training as well as test set is used for deployment using Flask RESTful API after appropriate fine-tuning. For the user interface, a web app has been created, where a user can upload an appropriate category of pictures to classify the respective kind of cancer.

This cancer-detecting system is developed to help patients and doctors to classify or identify various cancer classes. CNN can perform many image processing operations, increasing the speed of the procedure in comparison with classical techniques. These operations are very important in medical fields, where time is an important parameter that can help the surgeon both for diagnosis and before and during the surgical operation. The results of this project will help medical professionals to diagnose the presence of cancer using medical images and proceed with the appropriate course of treatment.

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II. LITERATURE REVIEW

Mahamudul Hasan, Surajit Das Burman, Samia Islam and Ahmed Wasif Reza [2] in their research paper has proposed a Convolutional Neural Networks(CNN) based approach for melanoma classification. The labelled images "benign" and "malignant" were used in this system. Images were changed to greyscale images. Images were put into the dataset relying upon their analysis mark which has been extracted from the metadata of the pictures. In the proposed system, there exist three layers. Input layer collects data that are delivering and adding some weight with it that goes to hidden layers. The neurons of the hidden layer separate the features from the data to find out a pattern. The pattern is then used as a basis to output layers that select appropriate classes. Finally, binary classification is used which appropriately select the class. They have evaluated the model performance using precision and f-score. The Precision and F1 scores of the proposed model were calculated to be 0.8325 & 0.8325.

Tanzila Saba, Muhammad Attique Khan, Amjad Rehman and Souad Larabi Marie-Sainte [3] proposed a new automated approach for skin lesion detection and recognition using a deep convolutional neural network (DCNN). The proposed cascaded design incorporates contrast enhancement through fast local Laplacian filtering (FlLpF) along with HSV color transformation, lesion boundary extraction using color CNN approach by following XOR operation and in-depth features extraction by applying transfer learning using the InceptionV3 model. The proposed method outperforms several existing methods and attained an accuracy of 98.4% on the PH2 dataset, 95.1% on the ISBI dataset and 94.8% on the ISBI 2017 dataset.

Khalid M. Hosny, Mohamed A. Kassem, and Mohamed M. Foaud [4] in their Research paper an automated skin lesion classification method is proposed.In this method a pre-trained deep learning network and transfer learning are utilized.The transfer learning is applied to AlexNet by replacing the last layer by a softmax to classify three different lesions (melanoma, common nevus and atypical nevus).According to the transfer learning, the weights of the modified model were fine-tuned in addition to the augmentation of the dataset images. The authors have concluded that their method has outperformed the existing methods with the achieved rates of 98.61%, 98.33%, 98.93% and 97.73% for accuracy, sensitivity, specificity, and precision respectively.

Waffa Alakwaa et al. [5] proposed a deep convolutional neural network (DCNN) architecture to detect nodules in patients with Lung Cancer and detect the interest points using U-Net Architecture. This step is a preprocessing step for 3D CNN. The deep 3D CNN models performed the best on the test set. While Waffa Alakwaa achieved a state-of-the-art AUC of 0.83, As an interesting observation, the first layer is a preprocessing layer for segmentation using different techniques. Threshold, Watershed, and U-Net are used to identify the nodules of patients. Raw image patches can be used to train the network from start to finish. The availability of a training database is the most important need, although no assumptions are made regarding the objects of interest or the underlying image modalities.

V Thamilarasi and, R Roselin [6] in their Research paper proposed Normal computer-aided techniques provide more methods for pathological diagnosis, segmentation and classification which takes more time and tedious work. DNN provides outstanding performance in medical image processing. Their Research paper proposed a basic and simple mechanism for the classification of lung images and attain an accuracy of 86.67%. With more images, it is possible to attain high accuracy. In future extend this type of work for segmentation and classification executed in various CNN methods and activation functions.

Milica M. Badža and Marko ˇC.Barjaktarovica[7] developed a new CNN architecture for brain tumor classification was presented in this study.The classification was performed using a T1-weighted contrast-enhanced MRI image database which contains three tumor types. The designed neural network is simpler than pre-trained networks, and it is possible to run it on conventional modern personal computers. The best result for 10-fold cross-validation was achieved for the record-wise method and, for the augmented dataset, and the accuracy was 96.56%.

S. Shivhare, Shikhar Sharma and Navjot Singh [8] presented a fully automated strategy for segmentation of brain tumors by making use of parameter-free K-means clustering algorithm and mathematical morphological operations like dilation and ho1e filling. The proposed strategy is used on the training dataset of Brats 2015. The tumor segmented using the presented approach is correlated with the ground truth result available in the dataset. The obtained results showed 75% of Dice Similarity Coefficient (DSC) with the available ground truth

Simon Hadush Nrea, Yaecob Girmay Gezahegn, Abiot Sinamo Boltena and Gebrekirstos Hagos [9] in their paper, used breast mammograms to detect mass regions and classified them into benign and malignant abnormalities. The authors have passed the images through different filters such as Gaussian filter, median filter and bilateral filter in the pre-processing process. They have proposed a CNN model and compared its performance with VGG based faster R-CNN. They have compared the models on the basis of detection accuracy, specificity and AUC-ROC value and their study shows that their proposed model achieved 91.86% detection accuracy, 94.67% sensitivity and an AUC-ROC score of 92.2%.

Fabio Alexandre Spanhol, Luiz S. OliveiraCaroline Petitjean and Laurent Heutte [10] in their research have used AlexNet CNN architecture on breast cancer histopathological images. In their work, they have also proposed several other strategies for training the CNN architecture, based on the extraction of patches obtained randomly or by a sliding window

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mechanism. They have magnified the images for better results. They have compared accuracy of the model on magnified images on different scales. Their experimental results showed that the CNN model performed better at classifying the histopathological images.

Hongdou Yao, Xuejie Zhang, Xiaobing Zhou and Shengyan Liu[11] in their paper have used 3 breast cancer histology dataset and have proposed two deep learning models using two different types of neural networks. One is a CNN(DenseNet) model and the other is A RNN(LSTM) model. They have trained the models separately on the datasets and have introduced the TTA method in the testing phase. The metrics that have been used by them to compare the performance of the models are classification accuracy, precision, recall and F-1 score. They have compared the models on the three datasets separately. The authors have concluded that their models have achieved state-of-art results using CNN and RNN with attention mechanisms.

Tomas Iesmantas and Robertas Alzbutas[12] in their paper authors present a deep learning solution, based on convolutional capsule network, for classification of four types of images of breast tissue biopsy when hematoxylin and eosin staining is applied. They have used breast histopathological images. The authors have used convolutional capsule neural networks to classify normal tissue and carcinoma. They evaluated the model using cross-validation accuracy. Although no regularization is considered while modelling, the cross-validation accuracy of their model is 87%.

S. Karthik, R. Srinivasa Perumal and P. V. S. S. R. Chandra Mouli [13] have presented a computer-aided diagnosis using deep neural network(DNN) for breast cancer classification along with recursive feature elimination(RFE). They have compared the results with existing models such as SVM-RBF, EM-PCA-CART, ART-1, LP-SVM and have compared theri classification accuracy on various fold on the data.The performance of their proposed system is measured based on accuracy, sensitivity, specificity, precision, and recall. From the results, the accuracy obtained 98.62%.

Vimal Kurup R, V. Sowmya and K. P. Soman [14] analyzed the effect of pre-processing methods on the performance of capsulenet for brain tumor classification.In capsulenet there is pose (translational and rotational) relationship between simpler features that make up a higher level feature which results in better performance than conventional CNN architectures.When the architecture is applied on pre-processed data the accuracy obtained was 92.6%.

A. Asuntha, A.Brindha, S.Indirani and Andy Srinivasan [15] in their Research Paper proposed a method for segmentation of MRI, CT and Ultrasound images. The necessary features collected for the two photos are studied to correctly identify cancer cells. Ultrasound pictures are also used to check the system's legitimacy. They used feature selection as well as PSO, Genetic Optimization, and the SVM method, which resulted in an accuracy of 89.5 percent and a decrease in false positives.

III. METHODOLOGY

The following methodology will be followed to achieve the objectives defined for the proposed research work: Image data on four common cancers will be collected. They are as follows:

- Breast cancer Histopathological images [16]
- Lung cancer CT scan images [17]
- Brain Tumor MRI images [18]
- Skin pigmented lesion images [19]

A detailed study and analysis of the datasets are carried out to make the classification models. Data Augmentation is applied to the images of the dataset before modelling to achieve better results. A custom model constructed for each dataset using Keras Sequential API and two pre-trained models: ResNet-50 and Inception-V3 has been trained on the images using transfer learning. [20] The training results of the model is evaluated on the classification accuracy, precision, recall f-score and AUC value.

The models have been fine-tuned and will be trained again based on the evaluation of the test set for better results. On achieving the desired results, the best model is evaluated again and the evaluations have been visualized. The visualizations and a comparison between the models trained on the dataset have been done on the test set for metrics validation on unseen data. The best model has been used for deployment using Flask RESTful API. A web app is developed for ease of using the DCNN models by consumers for cancer detection using the respective type of images for different cancer types. The proposed methodology of the project is summarized in Fig 1.

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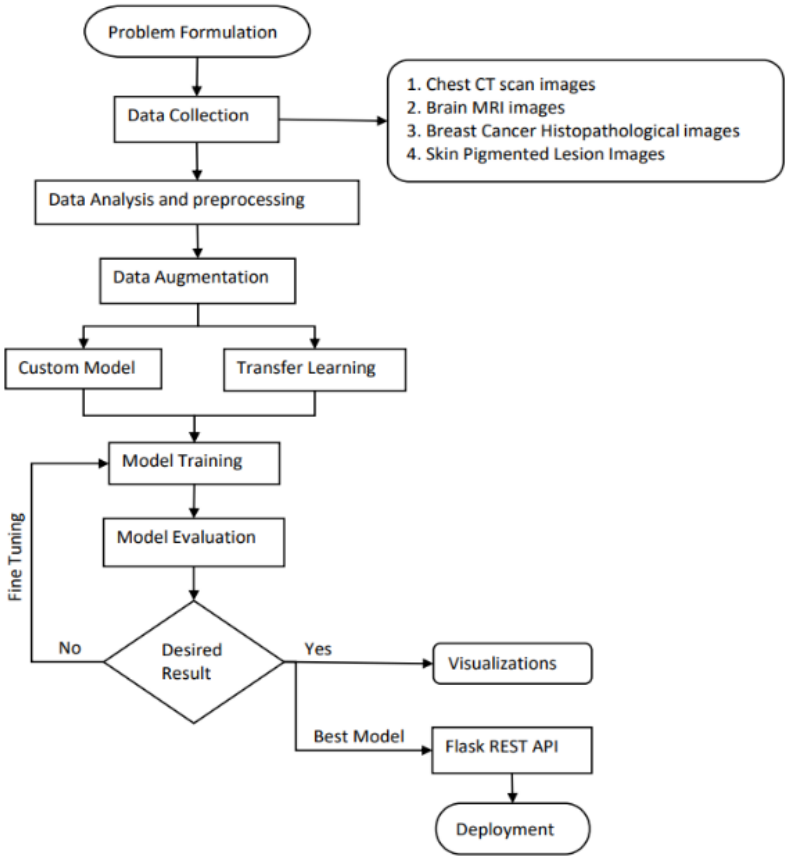

Fig 1. Flowchart of Proposed Methodology

A. The Datasets.

The details regarding the datasets used in designing and training the classification models mentioned in the methodology above are presented in Figures 2 and 3.

Figure 2 depicts the number of images belonging to each class of each dataset. Figure 3 shows the percentage of images in each class of each dataset. Both the images depict how balanced the datasets are. These are important information that will be used while deciding the classification metrics and evaluation of the proposed models.

1) Breast Cancer Histopathology Dataset:

Invasive Ductal Carcinoma (IDC) is the most common subtype of all breast cancers. To assign an aggressiveness grade to a whole mount sample, pathologists typically focus on the regions which contain the IDC. As a result, one of the common pre-processing steps for automatic aggressiveness grading is to delineate the exact regions of IDC inside of a whole-mount slide. The original dataset consisted of 162 whole mount slide images of Breast Cancer specimens scanned at 40x. From that, 277,524 patches of size 50 x 50 were extracted (198,738 IDC negative and 78,786 IDC positive). The dataset used for the proposed DCNN model consists of 25,000 images of each class. The used subset of the data is a class balanced dataset. The images are in RGB color format

2) Chest CT-Scan images dataset:

The dataset consists of four classes, three of common lung cancer types: Adenocarcinoma, Squamous Cell Carcinoma, Squamous cell carcinoma and one class of healthy lung CT-scan images. Lung adenocarcinoma is the most common form of lung cancer accounting for 30 per cent of all cases overall. Adenocarcinomas of the lung are found in the outer region of the lung in glands that secrete mucus and help us breathe. Large-cell undifferentiated carcinoma lung cancer can be found anywhere in the lung. This type of lung cancer usually accounts for 10 to 15 per cent of all cases of NSCLC. Squamous cell carcinoma type of lung cancer is found centrally in the lung. Squamous cell lung cancer is responsible for about 30 per cent of all non-small cell lung cancers. The dataset contains 1,000 images in the RGB color format. 338 images belong to the adenocarcinoma class, 187 images belong to the Large cell class, 260 belonging to the squamous class and 215 images are of healthy lungs. The dataset is a little unbalanced.

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3) Brain Tumor Images Dataset:

The brain tumor dataset consists of brain MRI scans. This dataset consists of 3,064 T1-weighted contrast-enhanced images from 233 patients. The data consists of three common types of brain tumors: Meningioma, Glioma and pituitary tumor. 708 images belong to the meningioma class, 1,426 images belong to glioma classes and the pituitary tumor class have 930 images. The images are in RGB color mode and are slightly class imbalanced.

4) Skin Lesions Dataset:

The dataset consists of 3,297 pigmented skin lesions images of melanoma belonging to two classes: benign and malignant. The dataset is filtered from the ISIC melanoma archive. The dataset consists of 1,800 images belonging to the benign class and 1,497 images belonging to malignant images. The dataset is slightly class imbalanced and the images are of RGB format.

The sample images of the four datasets are presented in fig 2.

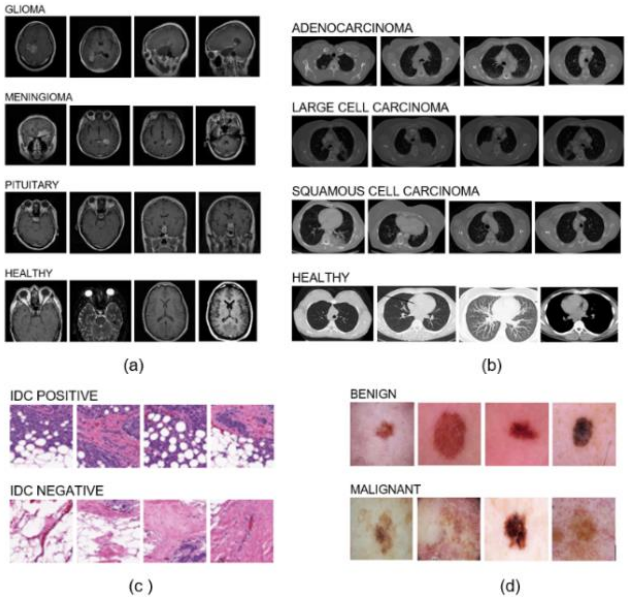

Fig 2. Sample images belonging to (a) Brain MRI Image, (b) Chest CT-Scan images, (c) Breast Cancer Histopathology, (d) Skin Lesions

B. Pre-processing.

The images in the mentioned datasets are in RGB format with pixels values in the range [0,255]. This poses a problem while initializing weights in the neurons of the CNN model. Without scaling, the high pixel range images will have a large number of votes to determine how to update weights. We rescaled the images from [0,255] to [0,1] using a rescaling factor of 1/255. Scaling every image to the same range [0,1] will make images contribute more evenly to the total loss. The number of images in [16][17][18][19] is not sufficient to train an image classifier to predict cancer accurately in real-time. Image augmentation is used to artificially increase the size of the datasets to generalize the prediction and increase the prediction accuracy of new unseen data. The existing images are slightly altered to create more images to train the DCNN models on. The augmentation. The augmentation parameters used during the training of the images are mentioned in table I. The size of images for training the DCNN models is changed based on the size of images in each dataset. For [17][18][19][20], each image is resized to 75×75×3, 75×75×3, 150×150×3, 224×224×3.

TABLE I USING DATA AUGMENTATION PARAMETERS AND VALUES.

Data Augmentation Parameter	**Parameter Value**
Rotation_range	20
Height_shift_range	0.2
Width_shift_range	0.2
Shear_range	0.2
Zoom_range	0.2
Vertical_flip	True
Horizontal_flip	True

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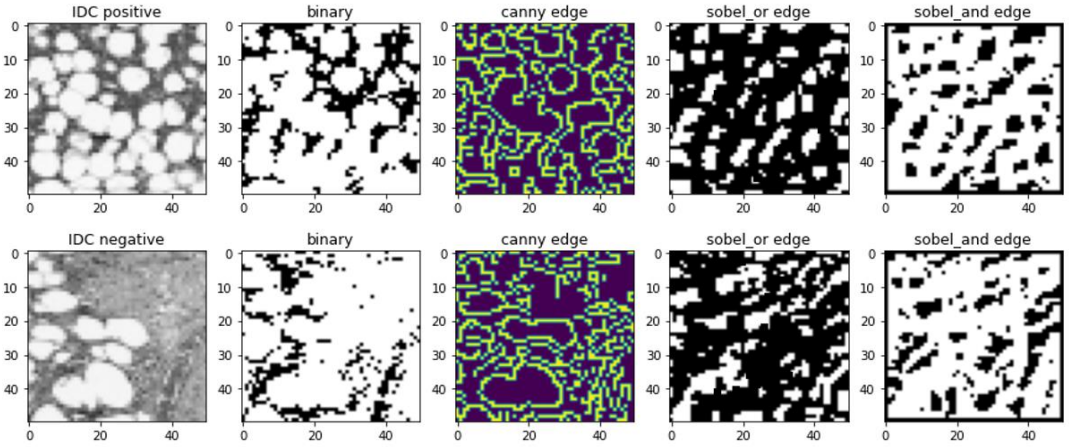

Fig 3. Binarized image, Canny edge detection and Sobel edge detection on Breast Cancer Histopathology images

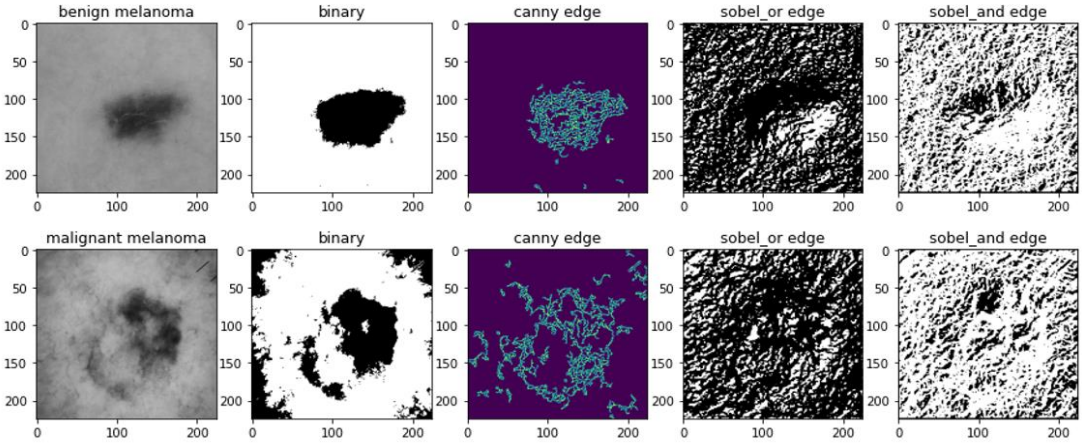

Fig 4. Binarized image, Canny edge detection and Sobel edge detection on skin lesion images

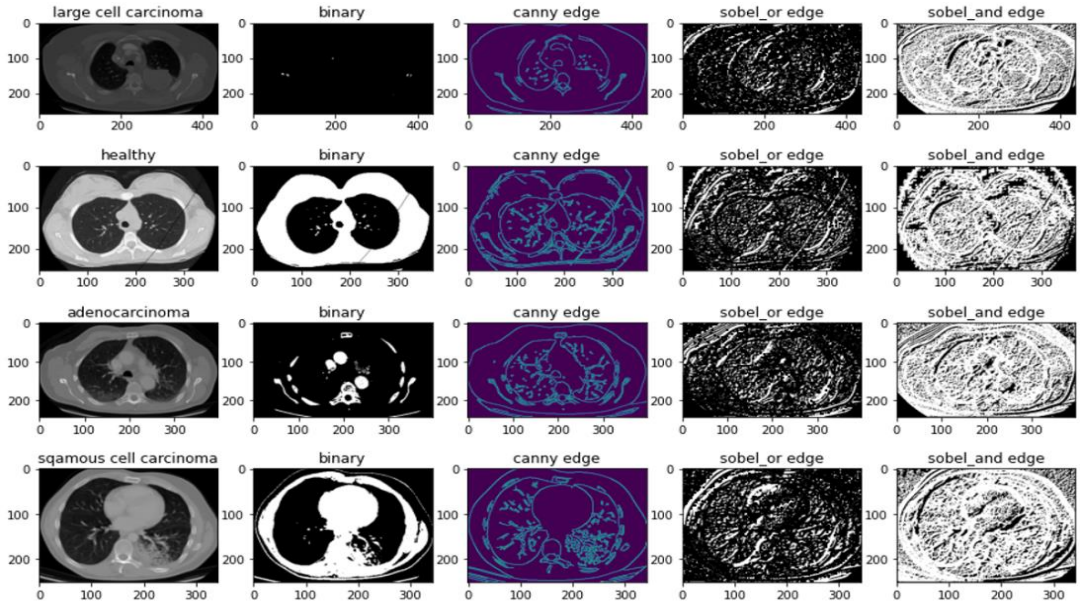

Fig 5. Binarized image, Canny edge detection and Sobel edge detection on chest CT-scan images

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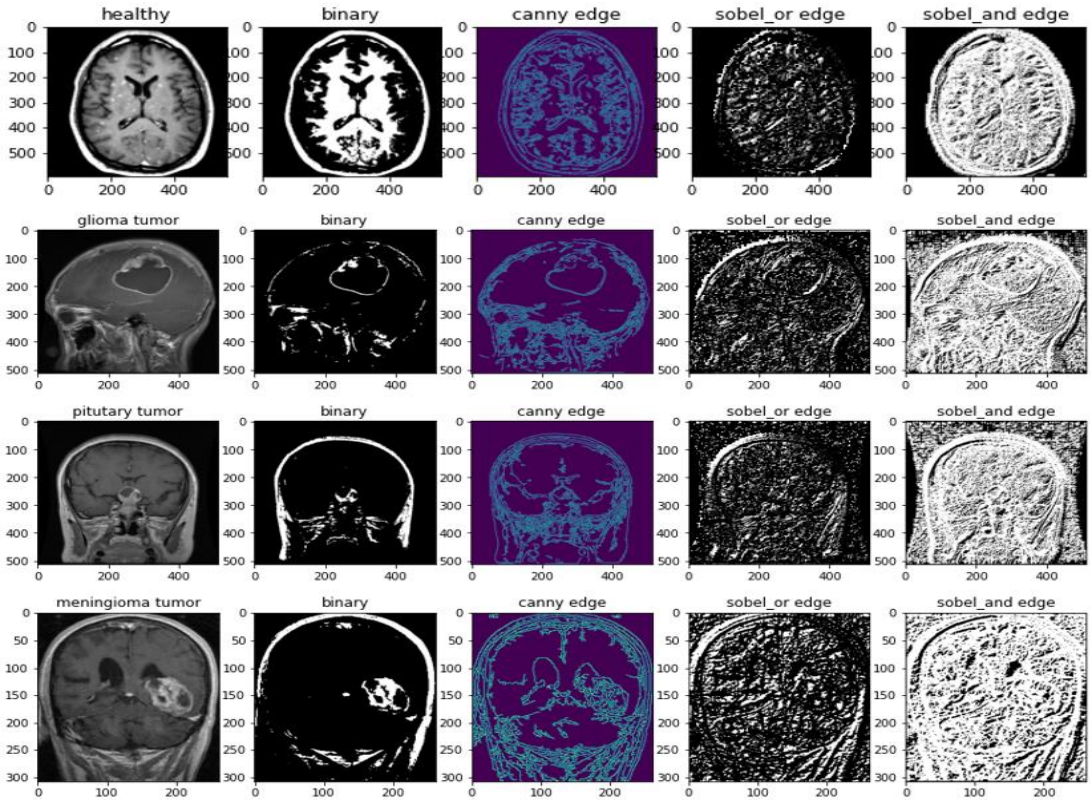

Fig 6. Binarized image, Canny edge detection and Sobel edge detection on brain MRI images

Canny edge detection is a multi-stage algorithm to detect to detect edges in images over a wide range. It is use to extract useful information from images and thus has a huge application in the dataset used in this project. The canny edge detection algorithm is implemented on all images from all the classes in the mentioned datasets. The edge detection algorithm is used to detect edges with lower error rate, which implies that the detection will capture as many edges present in the image. The first step of Canny edge detection algorithm is to reduce noise by applying Gaussian filter. It is followed by calculating the intensity gradients in the image. The spurious response to edge detection is eliminated using a gradient magnitude threshold. Potential edges are computed using double thresholding. The edges are tracked using hysteresis which will suppresses the weaker edges and give more value to the stronger ones. The upper and lower thresholds used for canny edge detection on the images in the dataset are 50 and 150.

Image binarization is a technique used to convert pixels of an image to only two values: 0 and 1 for black and white respectively. This technique is used in process to reduce background noise from the image. This process reduces computation that will be done on the image. Medical images uses image binarization to a great extent prior to application of CNN.

The Sobel edge is filter is an image processing technique used in edge detection algorithms. The Sobel operator performs a 2-D gradient measurement over the spatial features of the image. This is done so as to emphasize the regions with higher spatial frequency. Typically it is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The convolution kernel of 5x5 is used over the images. The kernel is used to maximise the response to the vertical and horizontal edges.

The operators mentioned above are shown in fig. 3, fig. 4, fig. 5 and fig. 6.

C. Transfer Learning.

The two pre-trained CNN models used for the comparison of the performance of the proposed models are ResNet-50 and Inception-V3.

ResNet-50[21] is a variant of the ResNet model. The architecture of ResNet-50 is similar to a bottleneck structure. The ResNet-50 architecture consists of a total of 50 layers of which 48 are Convolution layers along with 1 MaxPool and 1 Average Pool layer. It has 3.8 x 10^9 Floating points operations. The ResNet-50 model achieved a top-1 error rate of 20.47 per cent and achieved a top-5 error rate of 5.25 per cent on the ImageNet validation set.

Inception-V3 [22] is a variant of the Inception model. This model is 48 layers deep. The Inception-V3 architecture consists of about 23 million parameters. Inception-V3 reaches 21.2%, top-1 and 5.6% top-5 error for single crop evaluation on the ILSVR 2012 classification. In Inception-V3, various techniques have been suggested for network optimization such as

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factorized convolutions, regularization, dimension reduction and parallelized computations. These techniques have been used to loosen the constraints for easier model adaptation.

D. CNN Architecture.

1) BrecanNet:

BrecanNet is constructed to predict one of the following two predictions in breast histopathological images: IDC positive and IDC negative. The CNN model developed for breast cancer prediction is implemented using Keras deep learning library's sequential API [22]. The model contains 8 Convolution layers, 10 Batch Normalization layers,5 MaxPooling layers, 4 Dropout layers and 3 fully connected layers.

The CNN model consists of only 265,506 parameters out of which 263,586 are trainable and 1,920 are non-trainable parameters. It is 26 layered architecture. The input shape of the model indicates that the breast histopathology images used for training are of shape 75×75×3 having all three additive color spaces i.e. Red, green and blue. The output has a shape of 2 for the classification of 2 sample classes in the dataset. The small numbers of parameters of the model indicate that the proposed model is lightweight.

The proposed architecture comprises a heterogeneous mix of convolution layers with a kernel size of 3×3 and pooling layers of pool size 2×2. A varied filter size for the dimensionality of the output space is used in different convolution layers of the architecture. This architectural diversity of the CNN architecture provides a strengthened feature detection from the input histopathological images and enhances the representational capacity of the task of breast cancer prediction.

2) LungNet:

LungNet is constructed to predict one of the following predictions in Lungs CT-Scan images: Adenocarcinoma, Large-Cell-Carcinoma, Normal, Squamous-Cell-Carcinoma. The CNN model developed for lungs cancer prediction is implemented using Keras deep learning library's sequential API. The model contains 5 Convolution layers, 7 Batch Normalization layers, 3 MaxPooling layers, 2 Dropout layers and 3 fully connected layers.

The CNN model consists of only 2,584,452 parameters out of which 2,546,884 are trainable and 37,568 are non-trainable parameters. It is 23 layered architecture. The input shape of the model indicates that the breast histopathology images used for training are of shape 224×224×3 having all three additive color spaces i.e. Red, green and blue. The output has a shape of 4 for the classification of 4 sample classes in the dataset. The small numbers of parameters of the model indicate that the proposed model is lightweight.

The proposed architecture comprises a heterogeneous mix of convolution layers with a kernel size of 3×3 and pooling layers of pool size 2×2. A varied filter size for the dimensionality of the output space is used in different convolution layers of the architecture. This architectural diversity of the CNN architecture provides a strengthened feature detection from the input CT-Scan images and enhances the representational capacity of the task of lungs cancer prediction.

3) BrainNet:

BrainNet is constructed to predict one of the following three predictions in brain MRI-scan images: Meningioma, Glioma and Pituitary tumor. The CNN model developed for brain cancer prediction is implemented using Keras deep learning library's sequential API. The model contains 3 Convolution layers, 3 MaxPooling layers, 4 Dropout layers and 2 fully connected layers.

The CNN model consists of only 1,631,267 parameters out of which 1,631,267 are trainable and 0 are non-trainable parameters. The input shape of the model indicates that the T1-weighted contrast-imbalanced brain MRI-scan images used for training are of shape 150×150×3. The output has a shape of 3 for the classification of 3 sample classes in the dataset. The small numbers of parameters of the model indicate that the proposed model is lightweight. This architectural diversity of the CNN architecture provides a strengthened feature detection from the input images and enhances the representational capacity of the task of brain tumor prediction.

4) MelNet:

MelNet is designed to predict one of the following two predictions about the type of skin cancer using skin lesion images: Benign and Malignant tumor. The CNN model developed for skin cancer prediction is implemented using the sequential API of Keras' deep learning library. The model includes 9 convolution layers, 7 batch normalization layers, 5 MaxPooling layers, 1 dropout layer, and 6 fully connected layers.

The CNN model consists of 2,961,841 parameters, out of which 2,958,889 are trainable and 2,952 are non-trainable parameters. It is a 28 layered architecture. The model input layer shows that the skin lesion images used for training have a 75x75x3 shape with all three additive color spaces i.e. Red, green and blue. The output has a shape of 2 for the classification of 2 sample classes in the dataset.

The proposed architecture consists of a heterogeneous mixture of convolutional layers with a kernel size of 3x3 and pool layers with a pool size of 2x2. Different filter sizes for the dimensions of the output space are used in different convolution layers of the architecture. This architectural versatility of the CNN architecture provides enhanced feature recognition from input skin lesion images and enhances the ability to represent skin cancer prediction tasks.

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IV. RESULT AND OBSERVATION

A. Breast Cancer.

The performance of BrecanNet in terms of classification accuracy, loss, precision, recall, f-score and AUC score is compared to that of ResNet-50 and Inception-V3. The classification accuracy achieved by ResNet-50, Inception-V3 and the BrecanNet is 90.46%, 88.29% and 88.12% respectively. All the classification metrics of the models over training and test are presented in table II and table III respectively.

TABLE II-PERFORMANCE TESTED ON THE TRAINING SET USING THE THREE MODELS.

Models	Params	Accuracy(%)	Precision(%)	Recall(%)	F-Score	AUC
ResNet-50	25.6 M	90.46	90.46	90.46	0.9054	0.9671
Inception-V3	23.8 M	88.29	88.29	88.29	0.8838	0.9516
BrecanNet	265 K	90.14	90.14	90.14	0.9018	0.9642

TABLE III-PERFORMANCE TESTED ON THE TEST SET USING THE THREE MODELS.

Models	Params	Accuracy(%)	Precision(%)	Recall(%)	F-Score	AUC
ResNet-50	25.6 M	83.00	83.00	83.00	0.8299	0.9047
Inception-V3	23.8 M	87.77	87.77	87.77	0.8776	0.9481
BrecanNet	265 K	88.35	88.35	88.35	0.8838	0.9523

The results from the above two tables shows that the proposed model, BrecanNet is lightweight performs at par on the training set and works better as compared to ResNet-50 and Inception-V3 on the test set which are heavy models. Values of all the classification metrics of BrecanNet on the test set is better than the rest two pretrained models. The results from table 3 proves that the proposed model, BrecanNet performed better on unseen data than ResNet-50 and Inception-V3.
BrecanNet is trained on the GPU for 100 epochs using a batch size of 400 and achieved a training accuracy of 90.14% and a validation accuracy of 88.39%. Accuracy, loss, precision, recall, f-score and AUC of both training and validation set are visualized in Fig. 7.
It is visible from figure 7, that both the training and validation metrics tends to converge at the 100th epoch. It is clear from the accuracy and loss values of the training and validation set from figure that the model does not overfit. The fluctuations in the accuracy and loss validation data is not a big problem since the model has the freedom of choosing ways to classify the training data.
The precision, recall and f-score of the training and validation set converges at the 100^{th} epochs which shows that the proposed model correctly identifies images in the class-imbalanced dataset and correctly classifies and unseen data into the desirable classes. The AUC value of both the sets converges at the 100^{th} epoch as well. This proves that the proposed model's prediction quality is excellent.

B. Lung Cancer.

The performance of the Custom Model in terms of classification accuracy, the loss is compared to that of ResNet101V2 and Inception-V3. The classification accuracy achieved by ResNet101V2, Inception-V3 and the Custom is 81.27%, 91.17% and 82.66% respectively. All the classification metrics of the models on training and test are presented in Table IV and table V respectively.

TABLE IV-PERFORMANCE COMPARISON ON THE TRAINING SET USING LUNGNET.

Models	Accuracy(%)	Precision(%)	Recall(%)	F-Score	AUC
ResNet-50	81.27	86.73	83.29	0.8854	0.9628
Inception-V3	91.17	89.34	89.18	0.8927	0.9782
LungNet	63.70	59.28	61.28	0.6278	0.7818

TABLE V-PERFORMANCE COMPARISON ON THE TEST SET USING LUNGNET.

Models	Accuracy(%)	Precision(%)	Recall(%)	F-Score	AUC
ResNet-50	83.17	85.10	81.59	0.8320	0.9600
Inception-V3	88.57	88.54	87.25	0.8829	0.9694
LungNet	54.92	54.78	54.60	0.5472	0.7674

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C. Brain Tumor.

The performance of BrainNet in terms of classification accuracy, loss is compared to that of ResNet-50 and Inception-V3. The classification accuracy achieved by ResNet-50, Inception-V3 and the BrainNet is 97.76%, 98.30% and 79.07% respectively. All the classification metrics of the models over training and test are presented in table VI.

The results from the above two tables shows that the proposed model, BrainNet performs almost at par on the training and test set. BrainNet is trained on the GPU for 50 epochs and achieved a training accuracy of 79.07% and a validation accuracy of 72.58% , loss: 0.5038 , precision: 0.8214, recall: 0.7541 , auc: 0.9323 , f1_score: 0.7858 , val_loss: 0.7014 , val_precision: 0.7627, val_recall: 0.7258 , val_auc: 0.8865 , val_f1_score: 0.7438.All these parameters are visualized in fig.7.

TABLE VI PERFORMANCE TESTED ON THE TRAINING AND TEST SET USING THE THREE MODELS.

Models	**Training Set**		**Test Set**	
	Accuracy(%)	**Loss**	**Accuracy(%)**	**Loss**
ResNet-50	97.76	0.0657	86.94	0.4077
Inception-V3	98.30	0.0534	98.78	0.0556
BrainNet	79.07	0.5038	70.61	0.7359

It is visible from figure 7, that both the training and validation metrics tend to converge at the 50th epoch. It is clear from the accuracy and loss values of the training and validation set from the figure that the model does not overfit. The fluctuations in the accuracy and loss validation data is not a big problem since the model has the freedom of choosing ways to classify the training data.

The precision, recall and f-score of the training and validation set converges at the 50^{th} epochs which shows that the proposed model correctly identifies images in the class-imbalanced dataset and correctly classifies and unseen data into the desirable classes. The AUC value of both the sets converges at the 50^{th} epoch as well. This proves that the proposed model's prediction quality is excellent.

D. Skin Cancer.

Comparing MelNet's performance with respect to classification accuracy, loss, precision, recall, f-score, and AUC score with ResNet 50 and Inception V3 performance. The classification accuracy achieved by ResNet50, InceptionV3, and MelNet is , 66,67%, and 85.76%, respectively. All training and test classification metrics for the model are shown in Tables VII and VIII, respectively.

The results in the two tables above show that the proposed model MelNet is lighter, comparable in the training set, and works better than the heavier models ResNet 50 and Inception V3 in the test set. The scores of all MelNet classification metrics in the test set are better than those of the other two pretrained models. The results in Table 7 show that the proposed model MelNet outperforms ResNet 50 and Inception V3 for new unseen data. The MelNet is trained on a GPU for 300 epochs in 32 batch sizes, achieving 88.05% training accuracy and 85.76% verification accuracy. The accuracy, loss, precision, recall, f-score, and AUC of the training and validation set are shown in the figure. 7.

As you can see from Figure 7, both training and validation metrics tend to converge at the 300th epoch. From the accuracy and loss values of the training and validation set in Figure 5, it is clear that the model is not overfitted. The fluctuations in the accuracy and loss validation data is not a major issue, as the model is free to choose how to classify the training data.

Training and validation set's precision, recall, and f1 score converges at the 300th epoch. This shows that the proposed model correctly identifies the images in the class imbalanced dataset and correctly classifies the invisible data into the desired class. The AUC values for both sets also converge at the 300th epoch. This proves that the predicted quality of the proposed model is excellent.

TABLE VII-PERFORMANCE TESTED ON THE TRAINING SET USING THE THREE MODELS.

Models	**Params**	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F-Score**	**AUC**
ResNet-50	25.6 M	54.15	54.15	54.15	0.5312	0.5551
Inception-V3	23.8 M	50.45	50.45	50.45	0.5018	0.4831
MelNet	2.9 M	88.05	56.74	86.29	0.8634	0.9543

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TABLE VIII-PERFORMANCE TESTED ON THE TEST SET USING THE THREE MODELS.

Models	Params	Accuracy(%)	Precision(%)	Recall(%)	F-Score	AUC
ResNet-50	25.6 M	58.79	58.79	58.79	0.5636	0.7182
Inception-V3	23.8 M	66.67	66.67	66.67	0.6750	0.6452
MelNet	2.9 M	85.76	83.88	85.00	0.8339	0.9344

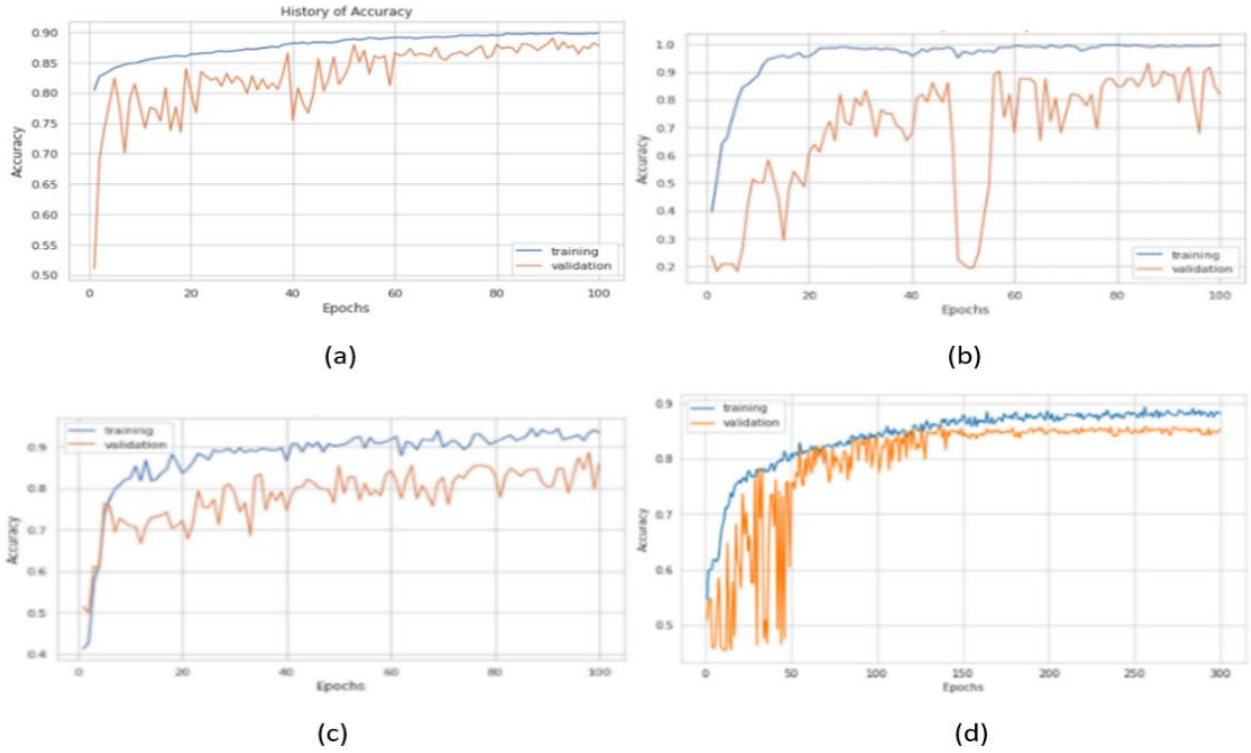

Fig 7. P Classification Accuracy of (a) BrecanNet, (b) LungNet, (c) BrainNet and (d) MelNet on training and validation set

V. CONCLUSION

In this project, four deep convolutional neural network architecture is proposed and designed for the detection of four common cancer types which is developed using TensorFlow backend and Keras deep learning library. Data augmentation is applied to the cancer images before training. The performance of the proposed models is compared to the performance of ResNet-50 and InceptionNet-V2. All the CNN architecture proposed are lightweight, having comparatively few parameters compared to the other ResNet-50 and InceptionNet-V2.

The effectiveness of BrecanNet is better than the other two pre-trained models for prediction of having better classification accuracy, precision, recall, f-score and AUC score on the unseen test set. MelNet has a classification accuracy of 88.35% on the unseen test set. The classification accuracy of BrainNet for the prediction of brain tumors is 70.61% on the test set. However, the performance of InceptionNet-V2 is better than the other two on the brain tumor test set. The effectiveness of MelNet is better than the other two pre-trained models for prediction of having better classification accuracy, precision, recall, f-score and AUC score on the unseen test set. MelNet has a classification accuracy of 85.76% on the unseen test set.

This is an end-to-end deep learning project. The project has significant value in the field of cancer prediction and diagnosis. Further, the deployment of the models can help in the ease of use for clinical diagnosis. The models presented can be used to predict the type of cancer in each cancer image. The results shown above will allow understanding and can help further research in this field. The use of deep learning for the diagnosis of the disease can decrease the use of other techniques for cancer prediction and can speed up the process of diagnosis. The automated prediction using deep learning models can speed up the time required for cancer diagnosis and prognosis.

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