Classification of Medical Images using Deep Learning

Romaisa Tariq[a], Najme Zehra Naqvi[b]

[a] *Indira Gandhi Delhi Technical University for Women, James Church, New Church Rd, Opp. St, Kashmere Gate, New Delhi, Delhi-110006, India. Email: romaisa019mtcse20@igdtuw.ac.in*

[b] *Indira Gandhi Delhi Technical University for Women, James Church, New Church Rd, Opp. St, Kashmere Gate, New Delhi, Delhi-110006, India. Email: najmezehra@igdtuw.ac.in*

Abstract: The advancement of technology is creating ease in every field and one of the major fields that has benefitted from this is healthcare. Medical images which includes Multi resonance images, Computed tomography scans and many more have always been used significantly to get a better understanding of the disease, rather knowing the disease and blurred visions of the same can be a matter of concern since so much depends on the images as they are used for analysation. The Covid19 Pandemic hit the population and made things worse for humans and created havoc worldwide, and its early detection using the chest X-rays is significant and the use of technology in this can make it an even better process. So, to classify the chest x-ray images into covid19, viral pneumonia, lung opacity or normal can play a notable role in the area of research. For the indicated purpose, a pretrained model is used by using transfer learning, an efficentnetb4 is used for the same. For the evaluation part of the model, F1 score, sensitivity and precision are used. The method successfully classifies the chest x-ray images into four types, accompanied by an accuracy of 96.73% on the test set. Brain tumor has also been an area of major concern for a long time and various research has been done in the indicated field, but still a lot is left to be discovered. The classification of brain tumors not only helps in creating ease with treatment, but it also depicts that if a tumor is cancerous or not. For this purpose, MRI images are being used for classifying brain tumors into glioma, pituitary, no tumor, meningioma and for this also, a pretrained model is used by using transfer learning, efficentnetb4 is used for the same and for the evaluation part of the model, F1 score, sensitivity and precision are used. The method successfully classifies the brain mri images into four types with accuracy of 98.58% on the test set. While most of the existing techniques either use different methods for same modality or different methods for different modalities, this work uses same method efficientnetb4 for both different types of medical images x-ray as well as mri images.

Keywords: Deep Learning; Medical Imaging; Image Modality; Chest X-ray; Brain Tumor.

1. Introduction

"The COVID-19 pandemic has created massive harm to society and caused panic across the world. Such panic may be ascribed to the apparently misleading capabilities of COVID-19." [1] "As a result, the severity of the causative coronavirus, SARS-CoV-2, changed to be deeply underestimated throughout society at the start of the COVID-19 outbreak" [1]. "Putting off care that delays detection, prognosis and remedy of great fitness situations can also additionally result in a faded niche of life, situations worsening in preference to being managed, or even deaths that might have in any other case been preventable. Detection and classification of covid19 will not only help doctors to help the patient sooner but it will help to increase the survival rate as well. When it comes to a medical decision which is image grounded, different modalities of medical images of a particular organ in a case are captured. Every image has a story to tell and these images will represent a modality that will give us the examined organ's details which could be a tumour or a stroke. The complete and accurate analysis of every modality promotes us in the right direction. Coronavirus ailment "is an infectious ailment" [1] "due to the SARS-CoV-2 virus. Most humans inflamed with the virus will revel in slight to mild breathing infection and get better without requiring unique treatment. However, a few turns" [1] "into severely sick and require scientific" [3] "attention and it affects the lungs severely and some people feel severe post covid19 affects too. Pneumonia" [4] "is contamination that inflames the air sacs in a single or each lung. The air sacs might also additionally fill with fluid or purulent material" [2][4], "inflicting cough with phlegm or pus, fever, chills, and problem in breathing." [2][4] "A style of organisms, which include bacteria, viruses and fungi, can purpose pneumonia." [2][4] "Pulmonary opacity is a nonspecific time period describing a place of elevated pulmonary attenuation as a result of an intraparenchymal process. Pulmonary opacification represents the end result of a lower within the ratio of fueloline to gentle tissue blood, lung parenchyma and stroma within the lung. The brain tumour has been a devasted form of disease and continues to be a reason of death for millions of people and brain itself has a structure of complexity and in addition to that, if a tumor happens to be located in the brain it makes things worse, as not only, it is one of the most important organs of the body but because it gives instructions to all other parts of the body and any discrepancy in the same will affect all other functions as well in some way or the other, the detection of "tumor in early stages" [20] can increase the chances of survival, now brain tumor can be benign or malign and this depends on the position, the nature of the tumor and how it is growing and it does not affect the healthy cells and does not make them cancerous therefore they are benign and instances can include pituitary and meningioma, malign brain tumor are cancerous and does affect the nearby cells and sometimes even affect the spinal cord too and instance includes glioma. Brain tumors also have stages based on how severe they are or how much they are growing. Early detection at early stages helps the patients to survive.

- This work classifies brain tumor as well as different lung diseases using brain mri and chest x-ray images respectively by utilising efficientnetb4 for both different types of medical images.
- Gives good accuracy.
- Different performance metrics to evaluate the work.

2. Related work

"Linda Wang et al. [5] proposed COVID-Net which is one of the first open source network designs for COVID-19 detection from CXR images and with this they also provided COVIDx which is an open source bench mark dataset. This dataset is combined and modified using 5 different publicly available repositories and the architecture is especially tailored for detecting covid19.The COVID-Net gave a sensitivity of 95.0, 94.0, 91.0 for Normal Non-COVID19 and COVID-19 respectively. COVID-Net gave positive predictive value of 90.5, 91.3, 98.9 for Normal Non-COVID19 and COVID-19 respectively." [5]

"Wei Wang et al. [6] proposed detection of COVID-19 by using Chest X-Ray Images and the technique used is MCFF-Net. MCFF-Net is basically based on the Parallel Channel Attention Feature Fusion Module. The overall accuracy of MCFF-Net66-Conv1-GAP is 94.66% for classification of 4 classes and with the classification accuracy, precision, sensitivity, specificity, and F1-score of COVID-19 100%." [6]

"Sharmila V J et al. [7] gave an algorithm of Deep Learning for COVID-19 Classification with the help of Chest X-Ray Images, it proposes a brand-new version of CNN and deep convolutional generative opposed networks (DCGANs) that classify CXR pictures into normal, pneumonia, and COVID-19. The proposed version carries 8 convolutional layers, 4 max-pooling layers, and absolutely related layers, which give higher outcomes than the present pretrained methods (AlexNet and GoogLeNet). DCGAN produces synthetic/faux pictures to conquer the demanding situations of an imbalanced dataset and along with this extracting deep functions of all pictures within the dataset. In addition, it enlarges the dataset and represents the traits of variety to offer an excellent generalization effect. In the experimental analysis, they used 4 wonderful publicly reachable datasets and thereby resulting in higher accuracy of 94.8%, 96.6%, 98.5%, and 98.6% than the existing pretrained models" [7]

"Md. Rezaul Karim et al. [8] gave out a deep covid19 explainer which explains COVID-19 Diagnosis Based on Chest X-ray Images and in this a deep neural network is proposed which is based on a method for automatic detection. In this, 15,959 CXR images of 15,854 patients, which covers normal, pneumonia affected, and COVID-19 affected cases are used. The images are first and foremost pre-processed, before they are being augmented and classified, which then comes to class-discriminating regions using gradient-guided class activation maps and layer-wise relevance propagation. The results show that the approach can identify COVID-19 with a PPV of 91.6%, 92.45%, and 96.12%; precision, recall, and F1 score of 94.6%, 94.3%, and 94.6%, respectively for normal, pneumonia, and COVID-19 cases, respectively" [8]

"Abdul Waheed et al. [9] proposed a data Augmentation which uses Auxiliary Classifier GAN for Improved Detection of Covid-19 in this an ACGAN based model called CovidGAN is utilised." [9] "Classification which is being conducted by using CNN alone, it yielded 85% accuracy and by an addition of synthetic images produced by CovidGAN." [9] "The accuracy even increased to 95%." [9]

"Kedong Rao et al. [10] brought a method which is based on SVRNet and SVDNet and uses lung x-rays and it is for the covid19 detection. In this, the most prominent classification models that are used for images are VGG16, ResNet50, InceptionV3, and Xception, and then fine-tuned and trained. Then, two new models for lung x-ray detection, SVRNet and SVDNet, were proposed on this basis. In the classification experiment of lung x-rays, it classified it into positive and negative for COVID-19, and the classification accuracy, sensitivity, and specificity of SVRNet and SVDNet are 99.13%, 99.14%, 99.12% and 99.37%, 99.43%, 99.31%, respectively." [10]

"Fatchul Arifin et al. [11] proposed a method for detection of covid19 by using single shot detection mobile net convolutional neural networks, the architecture that is being used in this is MobileNet's Single Shot Detection and this is being used because it has an advantage of the Single Shot Detection MobileNet models because they are lightweight and can be applied easily to mobile-based devices. The Single Shot Detection MobileNet V1 model can detect COVID-19 with an average accuracy of 83.7%, while the Single Shot Detection MobileNet V2 Single Shot Detection model can detect COVID-19 with an average accuracy of 87.5%." [11]

"Theodora Sanida et al [12] gave out a lightweight neural network which is for the detection of covid19 by using chest x-ray images and it is implemented on an embedded system, and for this purpose, MobileNetV2 is used, which is being modified and then compared it with standard mobile net v2 and the macro average for modified version gave 0.9688,0.9572, 0.9629 Precision, Recall and F1-Score respectively and the standard version gave 0.9033,0.9104, 0.9067 Precision, Recall and F1-Score respectively."[12]

"Ejaz Khan et al. [13] proposed a method for classification of covid19 which uses transfer learning and x-ray images in 3 methods and two strategies are being used for this. The 3 methods are EfficientNetB1, NasNetMobile, MobileNetV2. The accuracy of using strategy 1 panned out to be EfficientNetB1 92%, NasNetMobile 89.30%, MobileNetV2 90.03%and by using strategy 2, it emerged, for EfficientNetB1 96.13%, NasNetMobile 94.81% MobileNetV2 93.96%." [13]

"Sahil Lawton et al. [14] evaluated multiple techniques and thereby proposed that transfer learning techniques are better to detect viruses as compared to traditional methods. The model that performed the best was the VGG-19 which was implemented with the Contrast Limited Adaptive Histogram Equalization, on a SARS-CoV-2 dataset, and it achieved an accuracy of 95.75% and recall of 97.13%." [14]

"Muhannad Faleh Alanazi et al. [15] proposed a method for classification of brain tumor and for the indicated purpose, the method of CNN is being used by using MRI Images and the method achieved an accuracy of 95.75% on the same machine and accuracy of 96.83% on different machine on an unseen mri dataset." [15]

"Hanan Abdullah Mengash et al [16] proposed a method for brain tumor classification using CNN by using motion corrected MRI Images which gives more accuracy on motion corrected mri images than normal mri images for different folds the accuracy without motion corrected panned out to be

8-fold- 87.41, 10-fold- 93.60 .12-fold- 90.00 ,14-fold- 86.48 and cross validation accuracy with motion corrected mri images it is emerged as, for 8-fold -94.30 ,10-fold- 97.26 ,12-fold 91.45 ,14-fold-89.98." [16]

"Dillip Ranjan Nayak et al [17] gave a solution for classification of brain tumor using medical images and for the purpose, dense efficient net is used with added layers and the images were augmented for training and the accuracy resulted in 98.78% on the test set." [17]

"T. Ruba et al [18] used modified semantic segmentation networks (CNNs) based method for both types of images that is MRI and CT and tumor is then classified into 3 different categories using GoogLeNet CNN model. The accuracy for meningioma is 99.57%, for pituitary it is 99.56% and for glioma it is 99.78%." [18]

"Chelghoum, R et al [19] classified brain tumor into pituitary, glioma and meningioma and for this purpose used nine pretrained deep learning networks and got an accuracy of 98.71% on the test set." [19]

"Si-Yuan Lu et al [20] Resnet18 was used as the backbone with the proposed PBNET and 3 rnns are used for feature extraction for classifying of brain tumor and average accuracy of 97% was achieved." [20]

"Asma Naseer et al [21] CNN and computer aided diagnosis is used for classification purposes which gained an accuracy of 98.81% and the training has been done only on 28% of the data and 72% of data is being unseen and also utilises the augmentation technique." [21]

"Díaz-Pernas FJ et al [22] The approach that was used was multiscale CNN and as compared with other techniques, achieved a good accuracy of 0.973, it uses 3 processing pathways along with this, brain tumor segmentation is also conducted with a dice index of 0.828." [22]

"Badža MM et al [23] use a CNN approach for brain tumor classification and the network was evaluated using four approaches with an accuracy of 96.56%, the best result was obtained for 10-fold cross validation for the augmented dataset." [23]

3. X-ray images classification

3.1 Dataset

"The dataset used for education and assessment of the proposed method is publicly there on Kaggle" [24,25]. "This dataset has been revised multiple times" [24] and latest version, version 4 is used. "The cited dataset consists of more than one sub-dataset" [24], "with 4 exclusive classes, inclusive of COVID-19, lung opacity, normal and viral pneumonia." [24] Critically talking about the composition of the used dataset in element as it's far made with the aid of using merging exclusive datasets." [24] Each elegance is created with the aid of using merging exclusive sub datasets. "The elegance COVID-19 carries a complete of 3616 pictures, that are accumulated from 4 exclusive sources. The BIMCV-COVID19+" [26] "dataset in large part contributes to the used COVID-19 dataset with 2473 pictures" [26]. "It is one in all the most important unbiased datasets this is publicly to be had." [26] "Other datasets, which make contributions to this COVID-19 dataset, are the German Medical School dataset" [27] "with 183 chest X-ray pictures, whilst 560 chest X-ray pictures are accumulated from SIRM, GitHub, Kaggle, and Twitter" [28, 29, 30, 31]. "In addition, every other dataset is to be had on GitHub [32] containing four hundred chest X-ray pictures which have been merged." [32] "The RSNA pneumonia project dataset is one of the acknowledged chest X-ray datasets" [33]. "The RSNA dataset is composed of various lung abnormalities and wholesome lungs." [33] "The abnormalities varied from exclusive lung infections to lung cancer." [33] "It carries 26,684 chest X-ray pictures within the dicom format; in addition, the dataset is split into three main classes" [33]. "The biggest of those classes carries 11,821 pictures with exclusive lung infections and, of those, 6012 pictures are classified as non-COVID-19 lung infection (lung opacity), whilst 8851 pictures are normal and wholesome lungs" [33]. "The dataset is tested with the aid of using medical examiners primarily based totally on key symptoms, and scientific records is likewise taken into consideration during inspection, as it's far critical to recognise whether or not or now no longer the affected person has ever suffered from any correlated infections before. "The dataset is, in addition, prolonged with the aid of using, including 1341 everyday chest X-ray pictures, in conjunction with viral pneumonia chest X-ray pictures, is 1345 total in quantity and are sourced from" [34].

Table 1- Dataset details of chest x-ray images.

S.No.	Classes	Total data
1	Covid19	3616
2	Lung opacity	6012
3	Viral pneumonia	10,192
4	Normal	1345
5	Total	21,165

3.2 Method

The field of research concerning COVID19[41] has seen a lot of developments and improvisations lately, and the research has been done using CNN but not much research is done around this, as comparatively it is a newer field, transfer learning has also been used earlier, but there is a lot of scope in this field and an improved accuracy with a new type of technique in classification can be a contribution. "The Chest X-ray" [41] "dataset is accessed from Kaggle that includes 4 classes namely covid-19, viral pneumonia, lung opacity and normal images." [24]. This dataset has an imbalanced distribution of classes. If this is used as it is, it will give biased results for a particular class. For the same, the technique of augmentation [36] is used. This will make the dataset balanced [35] and will also increase the numbers. This will keep the original data as it is and will add more value to it. Horizontal flip data augmentation is used for this purpose. This is a crucial step as an imbalanced data leads to biased output. "The data is then divided into train, test and validation sets." [42] "The training set is used to train the model and test set is used to test the trained model. For this classification, Transfer Learning" [42] is used, this plays a significant role when there is not enough data to train the model, then pre-trained models come into existence because they have been trained on a corresponding data, it primarily gives a start point to the model.

For this EfficientNetB4[43] is used which returns a Keras image classification model, and the weights are pretrained on ImageNet. It uses batch normalization and dropout layer as well as regularization and this is evaluated on various parameters such as precision, sensitivity and F1 Score.

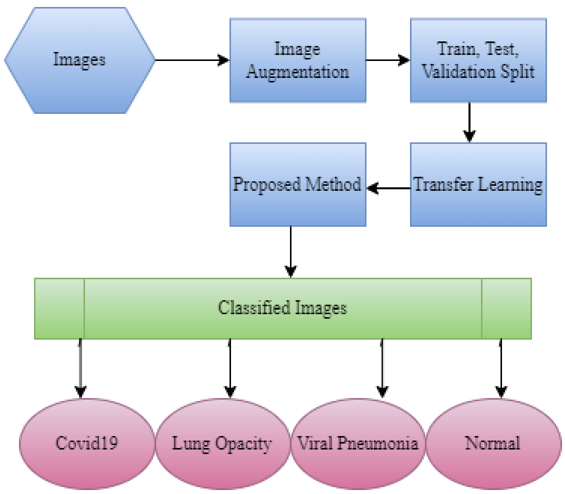

Fig 1 – Workflow of proposed method

3.3 Results

The results obtained are shown below, For evaluation purposes, sensitivity, precision and f1 score are used and for classification a pretrained efficientnetb4 is used which gives a high test accuracy of 96.73% and good training and validation accuracy as well, Precision, sensitivity and f1 score emerges to be 0.97 which is macro average and per class, precision of 1.00, 0.96, 0.93, 0.99 which is for covid19, lung opacity, normal and viral pneumonia respectively can be observed and achieving a per class sensitivity of 0.99, 0.94, 0.95, 0.99 for covid19, lung opacity, normal and viral pneumonia respectively and for per class F1 score it is 1.00, 0.95,0.94,0.99 for covid19, lung opacity, normal and viral pneumonia respectively.

Table 2 - Evaluation parameter results class wise.

Classes	Precision	Sensitivity	F1 Score
Covid19	1.00	0.99	1.00
Lung opacity	0.96	0.94	0.95
Normal	0.93	0.95	0.94
Viral pneumonia	0.99	0.99	0.99

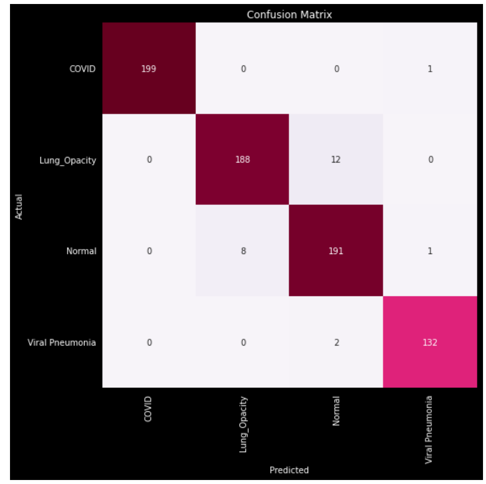

Fig 2 - Confusion matrix

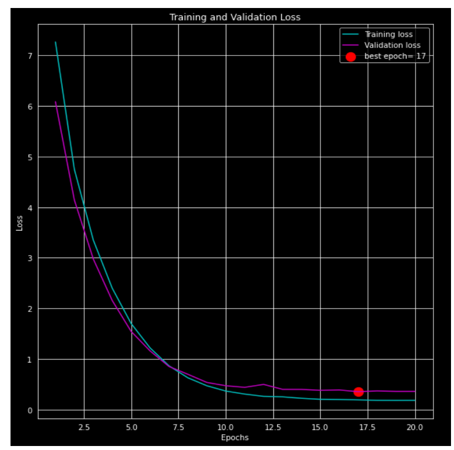

Fig 3 - Training and validation loss

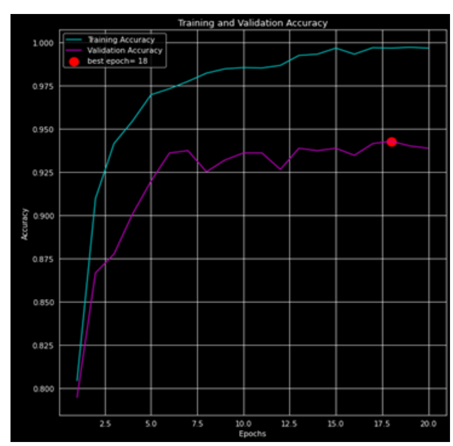

Fig 4 - Training and validation accuracy

In figure 2, confusion matrix is being represented and in figure 3, training and validation plot of loss, and the best epoch where loss is minimum, turns out to be epoch17 and the figure 4 represents training and validation plots and best accuracy turns out to be on epoch 18.

Table 3 - Comparison with existing techniques.

Method used	Accuracy	Sensitivity	F1 Score	Precision
Efficient NetB1 (With strategy II) [13]	96.13%	97.25%	96.50%	97.50%
CovidGAN [9]	Actual Data 85%	0.82	0.84	0.87
	Actual Data+ Synthetic Augmentation 95%	0.94	0.94	0.95
Efficientnet B4	**96.73%**	**0.97**	**0.97**	**0.97**

Table 4 – Pros and cons of the techniques.

Method	Pros	Cons
EfficientNetB1 (With strategy II) [13]	Uses multiple techniques.	Accuracy can be improved and larger dataset can be used
CovidGAN [9]	Enhanced Accuracy of covid19 detection.	Training can be improved further and larger dataset can be used
EfficientnetB4	**Improved Accuracy**	**Evaluation metrics can be improved further and larger dataset can be used.**

4. Mri images classification

4.1 Dataset

"The dataset used for the proposed method is publicly there on Kaggle" [37]. "The cited dataset consists of more than one sub-dataset" [37], with 4 exclusive classes, inclusive of glioma, meningioma, no tumor and pituitary. Critically talking about the composition of the used dataset**.** Each elegance is created with the aid of using merging exclusive sub-datasets. The glioma elegance contains 1621 images and meningioma contains 1645 images and 2000 images for no tumor elegance and 1757 images for pituitary elegance. "No tumor class was taken from Br35H" [38] dataset, this particularly contains yes, no, predicted images with 3060 files, the 'yes' folder contains 1500 images and the "no" folder contains 1500 images as well. "The glioma images were accessed from figshare dataset (version 5)." [39] "The figshare dataset contains 3064 T1-weighted contrast-enhanced images" [39] "from 233 patients' meningioma (708 slices), glioma (1426 slices), and pituitary tumor (930 slices)" [39] "and all other accessed from publicly available Kaggle dataset" [40], "this dataset contains a total of 3264 images, divided into four segments of pituitary, meningioma, glioma and no tumor." [40]

Table 5 - Dataset details for mri images.

S.no.	Classes	Training	Testing	Total data
1	Glioma	1321	300	1621
2	Meningioma	1339	306	1645
3	Pituitary	1457	300	1757
4	No Tumor	1595	405	2000
5	Total			7023

4.2 Method

The field of brain tumor classification has been a part of a lot of research work since a long time now and has seen a lot of advancements every now and then and CNN has been a major part of it including deep learning as well but a lot of work is left to be done and which can depict new and improved results on improvised and different datasets that are available. The dataset has been accessed from Kaggle [37] and it contains 4 different classes of brain tumor images and they are glioma which is cancerous in nature, meningioma and pituitary which is non-cancerous in nature, the dataset was balanced and divided equally into four classes and a class of no tumor. The data is then divided into train, test and validation sets. "The training set is used to train the model and test set is used to test the trained model" [42]. "For this classification" [42], Transfer Learning [42] this plays a significant role when there is not enough data to train the model, then pre-trained models come into existence because they have been trained on a corresponding data, it primarily gives a start point to the model. For this EfficientNetB4[43] is used which returns a Keras image classification model, and the weights are pretrained on ImageNet, dropout with a rate of 0.25 then with 0.2 and pooling and Dense layers were added with activation of relu and softmax, considering Adam as the optimizer and this is tested on various parameters of precision and sensitivity and F1 score.

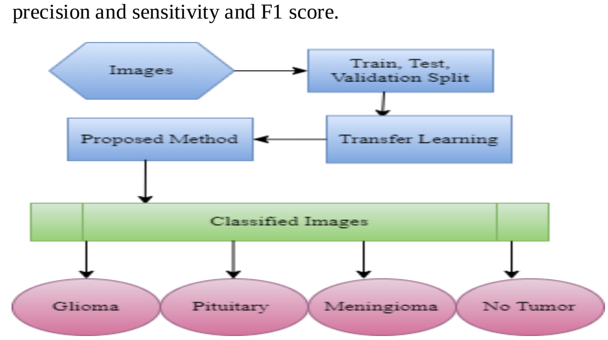

Fig 5 – Workflow of proposed method

4.3 Results

The results obtained are shown below, for the evaluation purposes sensitivity, precision and f1 score is used and for classification a pretrained efficientnetb4 is used which gives a high test accuracy of 98.58% and good training and validation accuracy as well, Precision, sensitivity and f1 score panned out to be 0.99 as macro average and per class the precision is 0.98, 0.97, 0.99, 1.00 for glioma, meningioma, pituitary and no tumor respectively and it also achieves a per class sensitivity of 0.98, 0.98, 0.98, 1.00 for glioma, meningioma, pituitary and no tumor respectively along with per class F1 score of 0.98, 0.97,0.99,1.00 glioma, meningioma, pituitary and no tumor respectively.

Table 6- Evaluation parameter results class wise.

Classes	Precision	Sensitivity	F1 Score
Glioma	0.98	0.98	0.98
Meningioma	0.97	0.98	0.97
Pituitary	0.99	0.98	0.99
No Tumor	1.00	1.00	1.00

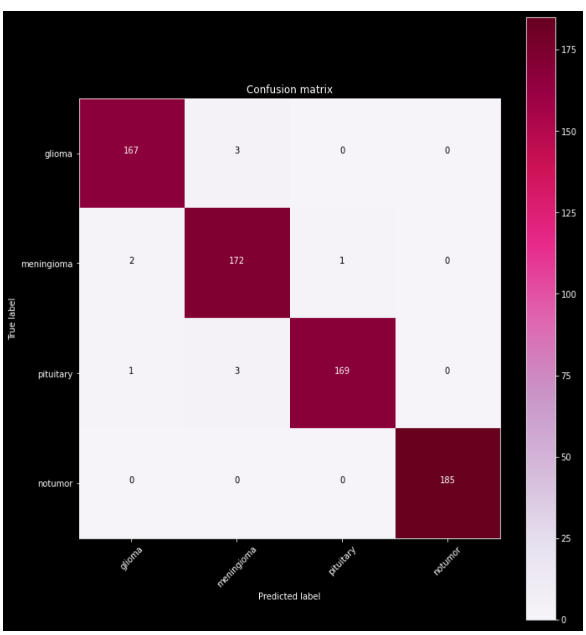

Fig 6 - Confusion matrix

In figure 6, confusion matrix is being depicted and in fig 7, it represents the training and validation loss plot and fig 8 represents training and validation Accuracy Plot.

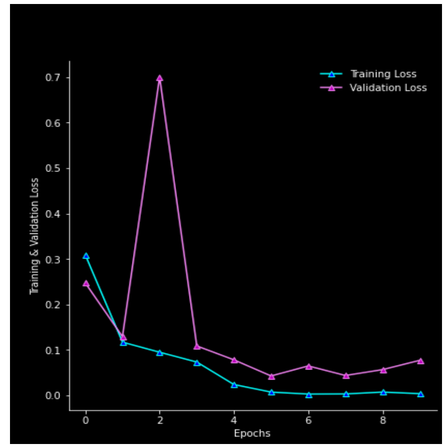

Fig 7 - Training and validation loss

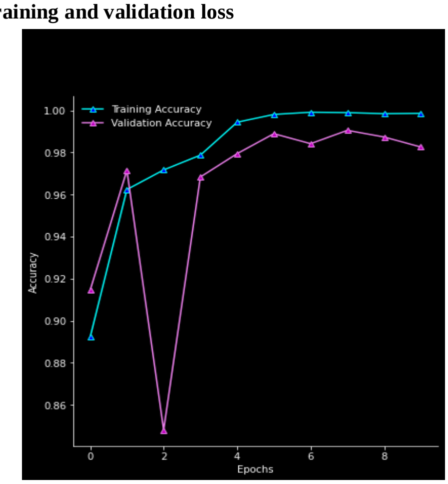

Fig 8 - Training and validation accuracy

Table 7 – Comparison with existing techniques.

Method used	Accuracy	Sensitivity	F1 Score	Precision
PBTNET with Resnet18 as backbone [20]	97% [20]	99.64	96.62	93.84
Dense Efficient Net [17]	98.78% [17]	-	98.75	98.75
Efficient netb4	**98.58%**	**0.99**	**0.99**	**0.99**

Table 8 – Pros and cons of the techniques.

Method	Pros	Cons
PBTNET with Resnet18 as backbone [20]	Better accuracy than other methods.	More samples can be used.
Dense Efficient Net [17]	Good Accuracy and good evaluation metrics results	Better pre-processing technique can be applied, can be tested with a larger dataset.
Efficient netb4	**Improved Accuracy**	**Evaluation metrics can be improved further and larger dataset can be used.**

5. Conclusion

The transfer learning based deep learning method, which comes from the efficient net network, efficientnetb4, is chosen for the classification procedure and it uses two types of medical images. Chest x-ray images for the indicated purpose, with 4 classes: lung opacity, normal. covid19, viral pneumonia and the second type is, mri images, which also come with 4 classes, namely glioma, pituitary, meningioma and no tumor. The data was gathered from different sources and combined together and made publicly available from Kaggle. Data Augmentation is done to eradicate the bias ness in the data in classification of x-ray images, this model has used regularization, dropout, dense layers and different activations and optimizers as and when required as well and it gives good accuracy as compared to the other techniques, and for the second classification, similar procedure is followed which gives good accuracy as well. The deep learning network, efficientnetb4 is used to classify two different types of medical images that are x-ray and mri images which in turns classifies different types of lung diseases whether it be covid19, lung opacity, viral pneumonia or normal and brain tumours of different types namely glioma, pituitary and meningioma, or even no tumor. The proposed work has certain limitations too as it can be tested on larger datasets where the method can be better evaluated, the method is tested on certain evaluation parameters but not on all frequently used evaluation parameters. In the Future, the accuracy can be improved further to enhance the classification of medical images. It can be used with other medical imaging modalities as well and further larger datasets can be used for this purpose.

References

Ji, T.; Liu, Z.; Wang, G.; Guo, X.; Lai, C.; Chen, H.; Huang, S.; Xia, S.; Chen, B.; Jia, H.; et al. Detection of COVID-19: A review of the current literature and future perspectives. Biosens. Bioelectron. 2020, 166, 112455.

Obaro, S.K.; Madhi, S.A. Bacterial pneumonia vaccines and childhood pneumonia: Are we winning, refining, or redefining? Lancet Infect. Dis. 2006, 6, 150–161.

Ibrahim, A.U.; Ozsoz, M.; Serte, S.; Al-Turjman, F.; Yakoi, P.S. Pneumonia Classification Using Deep Learning from Chest X-ray Images during COVID-19. In Cognitive Computation; Springer: Berlin/Heidelberg, Germany, 2021; pp. 1–13.

Marrie, T.J.; Durant, H.; Yates, L. Community-acquired pneumonia requiring hospitalization: 5-year prospective study. Rev. Infect.Dis. 1989, 11, 586–599

Linda Wang1,2,3*, Zhong Qiu Lin1,2,3, and Alexander Wong1,2,3, arXiv:2003.09871v4 [eess.IV] 11 May 2020, “COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases, from Chest X-Ray Image”.

Wei Wang, Yutao Li, Ji Li, Peng Zhang, and Xin Wang , “Detecting COVID-19 in Chest X-Ray Images via MCFF-Net” Hindawi, Computational Intelligence and Neuroscience, Volume 2021, Article ID 3604900, 8 pages.

Sharmila V J and Jemi Florinabel D “Deep Learning Algorithm for COVID-19 Classification Using Chest X-Ray Image”, Hindawi, Computational and Mathematical Methods in Medicine,Volume 2021, Article ID 9269173, 10 pages.

Md. Rezaul Karim, Till Döhmen, Dietrich Rebholz-Schuhmann, Stefan Decker, Michael Cochez, Oya Beyan,“DeepCOVIDExplainer: Explainable COVID-19 Diagnosis Based on Chest X-ray Images”,arXiv:2004.04582v3 [eess.IV] 6 Jun 2020.

ABDUL WAHEED, MUSKAN GOYAL, DEEPAK GUPTA, ASHISH KHANNA ,FADI AL-TURJMAN, AND PLÁCIDO ROGERIO PINHEIRO, “CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid-19 Detection”, date of publication May 14, 2020, date of current version May 28, 2020.

Kedong Rao, Kai Xie, Ziqi Hu, Xiaolong Guo, Chang Wen, and Jianbiao He "COVID-19 detection method based on SVRNet and SVDNet in lung x-rays," Journal of Medical Imaging 8(S1), 017504 (30 August 2021).

Fatchul Arifin, Herjuna Artanto, Nurhasanah, Teddy Surya Gunawan, Fast COVID-19 Detection of Chest X-Ray Images Using Single Shot Detection MobileNet Convolutional Neural Networks, Journal of Southwest Jiaotong University.

MDPI and ACS Style, Sanida, T.; Sideris, A.; Tsiktsiris, D.; Dasygenis, M. “Lightweight Neural Network for COVID-19 Detection from Chest X-ray Images Implemented on an Embedded System”. Technologies 2022, 10, 37.

Khan, E.; Rehman, M.Z.U.;Ahmed, F.; Alfouzan, F.A.; Alzahrani,N.M.; Ahmad, J. Chest X-rayClassification for the Detection ofCOVID-19 Using Deep LearningTechniques. Sensors 2022, 22, 1211.

Sahil Lawton and Serestina Viriri, “Detection of COVID-19 from CT Lung Scans Using Transfer Learning”, Computational Intelligence and Neuroscience, Hindawi, 12 apr, 2021.

Alanazi, M.F.; Ali, M.U.; Hussain, S.J.; Zafar, A.; Mohatram, M.; Irfan, M.; AlRuwaili, R.; Alruwaili, M.; Ali, N.H.; Albarrak, A.M. Brain Tumor/Mass Classification Framework Using MagneticResonance-Imaging-Based Isolated and Developed Transfer Deep-Learning Model. Sensors 2022, 22, 372.

Hanan Abdullah Mengash and Hanan A. Hosni Mahmoud, “Brain Cancer Tumor Classification from Motion-Corrected MRI Images Using Convolutional Neural Network”, Computers, Materials & Continua Tech Science Press DOI:10.32604/cmc.2021.016907,2021.

Nayak, D.R.; Padhy, N.;Mallick, P.K.; Zymbler, M.; Kumar, S.Brain Tumor Classification UsingDense Efficient-Net. Axioms 2022,11, 34. https://doi.org/10.3390/axioms11010034.

Ruba T, Tamilselvi R, Beham M. P, Aparna N. Accurate Classification and Detection of Brain Cancer Cells in MRI and CT Images using Nano Contrast Agents. Biomed Pharmacol J 2020;13(3).

Chelghoum, R., Ikhlef, A., Hameurlaine, A., Jacquir, S. (2020). Transfer Learning Using Convolutional Neural Network Architectures for Brain Tumor Classification from MRI Images. In: Maglogiannis, I., Iliadis, L., Pimenidis, E. (eds) Artificial Intelligence Applications and Innovations. AIAI 2020. IFIP Advances in Information and Communication Technology, vol 583. Springer, Cham.

Lu S-Y, Satapathy SC, Wang S-H and Zhang Y-D (2021) PBTNet: A New Computer-Aided Diagnosis System for Detecting Primary Brain Tumors. Front. Cell Dev. Biol. 9:765654. doi: 10.3389/fcell.2021.765654.

Asma Naseer, Tahreem Yasir, Arifah Azhar, Tanzeela Shakeel, Kashif Zafar, "Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI", International Journal of Biomedical Imaging, vol. 2021, Article ID 5513500, 11 pages, 2021.

Díaz-Pernas FJ, Martínez-Zarzuela M, Antón-Rodríguez M, González-Ortega D. A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network. Healthcare (Basel). 2021;9(2):153. Published 2021 Feb 2.

Badža MM, Barjaktarović MČ. Classification of Brain Tumors from MRI Images Using a Convolutional Neural Network. Applied Sciences. 2020; 10(6):1999.

M.E.H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M.A. Kadir, Z.B. Mahbub, K.R. Islam, M.S. Khan, A. Iqbal, N. Al-Emadi, M.B.I. Reaz, M. T. Islam, "Can AI help in screening Viral and COVID-19 pneumonia?" IEEE Access, Vol. 8, 2020, pp. 132665 - 132676. https://www.kaggle.com/tawsifurrahman/covid19-radiography-database. (accessed on 1st February 2022).

Rahman, T., Khandakar, A., Qiblawey, Y., Tahir, A., Kiranyaz, S., Kashem, S.B.A., Islam, M.T., Maadeed, S.A., Zughaier, S.M., Khan, M.S. and Chowdhury, M.E., 2020. Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-ray Images.

BIMCV-COVID-19, Datasets Related to COVID-19's Pathology Course. 2020. Available online: https://bimcv.cipf.es/bimcvprojects/bimcv-covid19/#1590858128006-9e640421-6711 data.

COVID-19-Image-Repository. 2020. Available online: https://github.com/ml-workgroup/covid-19-image-repository/tree/master/png data.

Chen, R.; Liang, W.; Jiang, M.; Guan, W.; Zhan, C.; Wang, T.; Tang, C.; Sang, L.; Liu, J.; Ni, Z.; et al. Risk factors of fatal outcome in hospitalized subjects with coronavirus disease 2019 from a nationwide analysis in China. Chest 2020, 158, 97–105.

Weng, Z.; Chen, Q.; Li, S.; Li, H.; Zhang, Q.; Lu, S.; Wu, L.; Xiong, L.; Mi, B.; Liu, D.; et al. ANDC: An Early Warning Score to Predict Mortality Risk for Patients with Coronavirus Disease 2019. J. Transl. Med. 2020, 18, 328.

Liu, J.; Liu, Y.; Xiang, P.; Pu, L.; Xiong, H.; Li, C.; Zhang, M.; Tan, J.; Xu, Y.; Song, R.; et al. Neutrophil-to-lymphocyte Ratio Predicts Severe Illness Patients with 2019 Novel Coronavirus in the Early Stage. medRxiv 2020.

Huang, I., Pranata, R. Lymphopenia in severe coronavirus disease-2019 (COVID-19): systematic review and meta-analysis. *j intensive care* **8,** 36 (2020).

COVID-CXNet. 2020. Available online: https://github.com/armiro/COVID-CXNet data.

Kaggle. RSNA Pneumonia Detection Challenge. Available online: https://www.kaggle.com/c/rsna-pneumonia-detectionchallenge/data

Mooney, P. Chest X-ray Images (Pneumonia). 2018. Available online: https://www.kaggle.com/paultimothymooney/chest-xray pneumonia

Shorten, C.; Khoshgoftaar, T.M. A survey on image data augmentation for deep learning. J. Big Data 2019, 6, 60.

Dongmei Han, Qigang Liu, Weiguo Fan,A new image classification method using CNN transfer learning and web data augmentation,Expert Systems with Applications,Volume 95,2018,Pages 43-56,ISSN 0957-4174.

Msoud Nickparvar. (2021). <i>Brain Tumor MRI Dataset</i> [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/2645886. (Accessed on 3rd March)

Ahmed Hamada, Br35H :: Brain Tumor Detection 2020, https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection?select=no

Cheng, Jun (2017): brain tumor dataset. figshare. Dataset. https://doi.org/10.6084/m9.figshare.1512427.v5.

Sartaj Bhuvaji, Ankita Kadam, Prajakta Bhumkar, Sameer Dedge, & Swati Kanchan. (2020). <i>Brain Tumor Classification (MRI)</i> [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/1183165.

Parnian Afshar, Shahin Heidarian, Farnoosh Naderkhani, Anastasia Oikonomou, Konstantinos N. Plataniotis, Arash Mohammadi,COVID-CAPS: A capsule network-based framework for identification of COVID-19 cases from X-ray images,Pattern Recognition Letters,Volume 138,2020,Pages 638-643,ISSN 0167-8655.

Sajja Tulasi Krishna, Vignan's, Hemantha Kumar Kalluri, Deep Learning and Transfer Learning Approaches for Image Classification, International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-7, Issue-5S4, February 2019.

Mingxing Tan, Quoc V. Lear, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks" Xiv:1905.11946v5 [cs.LG] for this version, 11 Sep 2020.

Vardan Aggarwal, "Complete Architectural Details of all EfficientNet Models", https://towardsdatascience.com/complete-architectural-details-of-all-efficientnet-models-5fd5b736142, (accessed on 20th February,2022).