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Using Deep Learning Concept In Detection Of Various Deadly Diseases (Brain Tumor)*

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Abstract—
Early and accurate detection of deadly diseases from medical images is a major challenge in healthcare. In this paper, we develop a new methodology to solve this problem by using "Generative Adversarial Networks (GANs), Convolutional Neural Networks (CNNs) and Explainable Artificial Intelligence (XALI)" techniques. Using GANs to generate high quality synthetic medi- cal images extends the limited training data baseline, allowing the CNN model to improve performance. Next we designed our CNN model layered with multiple convolutional and pooling layers that can classifies the images into different disease categories such as brain tumor. "XAI techniques, such as Grad-CAM is incorporated to increase the understandable and transparency of the CNN model's decision making process." Grad-CAM produces localization maps distinguishing the prominent regions of the input images that are important for the classification. Combining GAN based data augmentation, CNN based image classification and XAI powered explainability have synergistically integrated to produce a robust and reliable detection system of deadly diseases from medical images. Overall, this research may serve as a major contribution to the field of medical imaging analysis and help towards designing more reliable, more impactful, AI driven diagnostic systems.
Index Terms—*Convolutional Neural Networks (CNNs), Med- ical Image Analysis, Disease Detection, Explainable Artificial Intelligence (XAI), Grad-CAM, GANs.*

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I. Introduction

Medical images are very important for finding and diagnos- ing serious diseases early on. This helps doctors give quick and effective treatments. But there's a big problem: there aren't enough labeled medical image datasets. This makes it hard to create deep learning models that are accurate and reliable.

To tackle this challenge, this research paper suggests using Generative Adversarial Networks (GANs) like done by [1], [2] and [3] along with Convolutional Neural Networks (CNNs). Using Deep Learning and CNN for image classification can improve the results of disease detection in various medical fields [4]. The goal is to boost the detection of various serious diseases from medical images.The GAN part will help create synthetic medical images. This way, we can grow the current dataset and improve how well the CNN model works. Also, an Explainable AI (XAI) section will be added to the CNN model so that doctors get clear explanations for disease diagnoses. This will help healthcare professionals understand how the model thinks and makes choices similar to [5], [6], [7].

By bringing together generative adversarial networks, con- volutional neural networks and explainable AI, this research aims to build a strong and clear deep learning diagnostic system. This system can reliably find serious diseases, which should lead to better patient results and progress in medical imaging analysis.

II. Literature Review

A. Related Work

- [8] proposed a method for classifying breast cancer. This involves using data augmentation alongside Generative Adversarial Networks (GAN) and Convolutional Neural Networks (CNN). The authors utilize well-known benchmark datasets, such as the "Mammographic Image Analysis Society (MIAS), Digital Database for Screening Mammography (DDSM), and INBreast". By applying GAN, they artificially expand the dataset, which is crucial for training the CNN to improve classification.The find- ings were impressive. The results indicate that employing GAN to create synthetic images for data augmenta- tion raised the classification accuracy significantly—from 69.85% with the original dataset to 94% when using augmented data combined with GAN. Moreover, the paper also addresses how breast regions and abnormalities are segmented.
- [9] embraces a convolutional neural network (CNN) for analyzing patient images in order to diagnose a specific disorder. The study highlights a number of steps in image editing that transformed the data for the CNN's input including image centering and preparatory conver- sion. The analysis reveals that applying the CNN allows for precise identification of images from both sick and healthy patients offering a helpful solution to identify the illness.
- [10] presents two datasets used for medical research: Medical histories along with imaging results from MRI. For the first dataset the features were sorted in order of relevance and relationship with the target feature via RFE. The dataset was into two parts; training and testing, as five machine learning algorithms utilized these features. The random forest method generated the most accurate results having a mark of 99% alongside scores of 98%, 100%, and 99%. Using both "(SVM) and (AlexNet)" models, classifications were performed on the features extracted from the second dataset through the AlexNet model. The combined algorithm of machine learning and deep learning outperformed the deep learning model (AlexNet) alone. Meticulous techniques such as SMOTE and KNNImputer along with t-SNE algorithm and RFE algorithm were employed within the solution.
- [11] demonstrates a protocol for analyzing COVID-19 cases via XAI methods with CXR images for transfer learning. The model predicts COVID-19 classification alongside an explanation using heatmaps. In this study, they applied XAI tools to help untrained audiences better understand a black box AI model with greater clarity and transparency. The proposed hybrid model provides two outputs: COVID 19 diagnosis, model decision explana- tion. The provided information about potential COVID-19 diagnoses and its decisions explain why it made these decisions. However, in this project the model is problematic when processing CXR images and demands its identification component. The findings indicate that AI analysis tools can support COVID-19 diagnosis in health- care settings while assessing reliability and understanding forecasts.
- [12] a new approach to evaluate synthetic images, to increase reliability and quality of synthetic images. The approach is carried out in two stages: evaluation done qualitatively and quantitative evaluation. To rate the quality of the synthetic images, the proposed method uses a modified version of the Fre´chet inception distance metric — the Fre´chet MedicalNet distance score. To evaluate the reliability of the images, the deep neural network is used. The results show that our proposed method is able to produce synthetic images of higher quality while still being highly reliable.
- [13] proposes a method for classifying chest X-ray im- ages using healthcare analytics with the aim of detecting COVID-19. The proposed method uses a trained CNN model which is customized with architecture details, local discriminant features using LIME, and transfer learning models. The method uses a dataset comprising chest X-ray images of different resolutions and compared with "state-of-the-art" approaches. The suggested method showed improved results and confusion matrices have also been provided to illustrate these results. However, the paper does not give a concise summary of its methods and results.
- [14] This paper goal was to construct a machine learning solution capable of distinguishing benign and malignant skin conditions. The proposed system used artificial neu- ral networks (ANN) to create a classifier and was tested on two datasets: "ISIC 2018 and PH2". The accuracy of the ANN algorithm was 87.30% using the "ISIC" 2018 dataset and 91.90% using the "PH2" dataset. The researchers applied regression analysis and a confusion matrix to assess the system's performance.
- [15] proposes a novel framework named MI-GAN for retinal vessels image segmentation and generation based on Generative Adversarial Network. The intro- duced framework acquires valuable characteristics from a small training set. For style transfer algorithms to work effectively the VGG-19 network produces feature descriptors. They used batch normalization to enhance the training of "the generator and discriminator" in the model. This approach surpasses earlier variations in terms of "AUC ROC AUC PR and Dice" coefficient indicated in Table 2. they demonstrated the segmentation performance of the method along with the leading existing technique DRIU. The introduced framework has the capacity to elevate the performance of image segmentation and yield realistic-looking images.
- [16] offers a total all-inclusive transparent AI framework for medical imagery identification and segmentation in healthcare 5.0 settings to support decentralized learning and ensure protection of data privacy and security.

This architecture links deep learning approaches and feder- ated transfer learning (FTL) for detecting COVID-19. The FTL-enabled CNN auto-encoder classifier efficiently cleans corrupted data from COVID-19 patients and cat- egorizes the information into five groups. With the help of the explainability module proposal,the scheme evalu- ates the classifier's prediction and explains the decision- making logic. A taxonomy of applications for EXAI is introduced along with a specific use-case framework in healthcare that merges distinct AI approaches. The framework developed demonstrated a high accuracy near 98% and provided clear explanations and classification while protecting data privacy.

- [17] This work outlines a technique for identifying prostate cancer at an early stage through deep learning. The technique requires modifying ADC maps at multi- ple b-values with a neighbor voxel method while also segmenting the prostate and producing color maps. The refinement of ADC maps enables training of the CNN. The paper presents the distinct layers present in CNN like convolutional layers and pooling layers. Experimental results indicate that the introduced framework provides ideal specificity for early identification of prostate cancer.

III. Proposed Solution

Because of the difficulties in medical image analysis (es- pecially in acquiring labeled dataset and interpretability), we combined state-of- the-art techniques to overcome these challenges, effectively. In light of the learned insights about GANs for data augmentation and XAI for medical diagnosis from the literature review, our proposed approach to improving detection performance in detecting fatal diseases on medical images involves combining these techniques with Convolu- tional Neural Networks (CNNs).

Our approach is to synthesize (generate) medical data using GANs that provides additional samples to the dataset thus making the CNN model more accurate and as seen in papers like [8], [18], [4]. it increases the classification accuracy by a larger margin than standaalone models. Furthermore, we use XAI techniques to generate explanations that are under- standable, following [11]. who used heatmaps for the disease diagnosis similar to work by [11], who employed heatmaps to interpret model decisions for COVID-19 diagnosis.

Our approach to bring together these state-of-the-art meth- ods hopes to provide strong, reliable, and interpretable deep learning model for designing automated diagnosis system. In addition to greatly improving the early diagnosis of lethal diseases, this system also gives healthcare providers clear explanations for why their model made a particular decision so that they can become better trusted and more reliable along the diagnostic chain. Our approach is unique as it aims to solve the existing problems in medical image analysis and provide a full fledge solution for early detection of diseases with precision.

GAN

Generative Adversarial Network (GAN) is a class of Deep Learning which comprises two neural network, "the Generator and the Discriminator", both learns from the other in an adversarial fashion to produce synthetic data that looks as similar as possible to real data.

In the light of our proposed solution, the GAN component is utilized to synthesize synthetic medical images, such as "X- rays, CT scans, and MRI scans", to use for augmentation of the current dataset like done by [19]. Generator network is trained to learn a distribution of realistic looking medical images that copies the distribution of the real data, the discriminator net- work is trained to distinguish the real data from the synthetic data.

The Generator network is trained to learn how to syntheti- cally create medical images which look realistic enough that they fool the Discriminator network. The Discriminator net- work, however, is also generating better ability to differentiate real and generated synthetic images.

The generator receives a random normal distribution and then works. As the generator doesn't have a reference point it generates a random distribution which it then outputs. At the same time, an actual sample, or ground truth, is given to the discriminator. A discriminator is rewarded to learn the real distribution of the sample. It evaluates the distribution of the generated sample of the generator and when given, it has the discriminator fed a generated sample from the generator and sees what goes in. The discriminator will output a value close to '1' = real, if the distribution of the generated synthetic sample is close to the original sample. If the distribution doesn't match or if they are not even close to each other, then the discriminator gives a value close to "0" = fake.

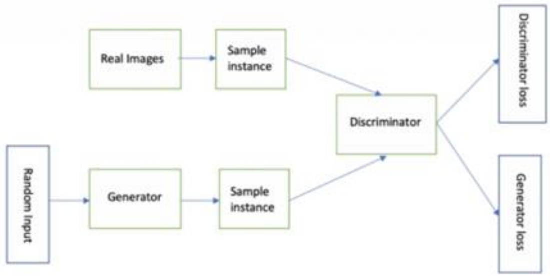

Fig. 1. Working of GAN

Generator: The network consists of several layers, including:
1) The 16x16x256 units, a leaky ReLU.
2) An output layer to change the output into 16x16x256 tensor through a reshape() layer.
3) Each followed by a leaky ReLU activation function, we use three convolutional transpose layers with 128, 64, and 32 respectively.
4) Lastly a convolutional layer with 3 filters (RGB channels of the image) and tan(h) activation function.

Discriminator: The network consists of several layers, in- cluding:
1) We have a layer of 32 filters then a leaky "ReLU activation function".
2) The network has three "convolutional layers" of 64, 128, and 256 filters each with a corresponding leaky ReLU activation function followed by stride 2.
3) The construct of a Flatten layer to convert the output into 1D tensor. dropout rate 0.4 in a dropout layer.
4) A single unit final dense layer with a "sigmoid activation function".

We used a binary cross entropy loss function and Adam optimizers (beta, learning rate of (0.5, 0.0002) respectively). For alternation between training the generator and discrimina- tor networks, the training process is alternated. The generator at each training iteration creates a batch of synthetic images, choosing simultaneously a batch of real images from the dataset. Next, the discriminator network is trained to separate real from synthetic images. The hope is that the generator can generate synthetic images that confuse (or are 'fool the discriminator') quite well.

Once the GAN is trained, we then pass a randomly generated noise vector through the generator network to generate synthetic images. These generated images can be used for augmenting the existing dataset which helps in improving the detection of deadly diseases from medical images using CNN model.

Generating Brain MRI Images using GAN:

Training Dataset- For this study, we utilized "the Brain Tumor MRI Dataset, a comprehensive collection of 7023 human brain MRI images", classified into four cate- gories: Sourced from the "figshare, SARTAJ and Br35H datasets" for "glioma, meningioma, no tumor and pitu- itary" from (Kaggle.com).

S.No.	Dataset Class	No. of Images
1	pituitary	1457
2	notumour	1595
3	meningioma	1339
4	glioma	1321

TABLE I
MRI TRAINING DATASET

The GAN model then trained on a training dataset of 5,712 images from the Brain Tumor MRI Dataset, rep- resenting a diverse range of brain MRI scans across the four classification categories.

After process of training, the GAN model was able to produce a batch of synthetic MRI images similar to the real images in the training dataset by introducing augmented data with high quality artificially generated sample. Here is the first 25 generated synthetic images:

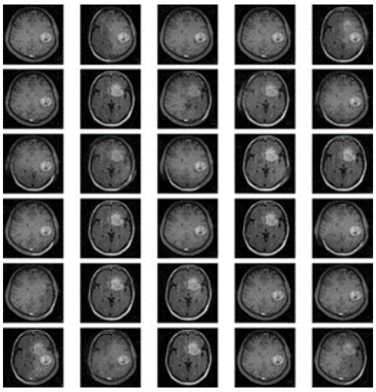

Fig. 2. Output of GAN for Brain Tumor MRI

CNN

After successfully creating synthetic images with the Gen- erative Adversarial Network (GAN), we then applied a Convo- lutional Neural Network (CNN) to categorise and diagnose the images for deadly diseases. However, CNNs have been wildly adopted in medical image analysis because of their excellent success in classification tasks on images. Feature learning, however, is typically difficult for CNNs because many images in their inputs can be geometrically or semantically similar. We designed a CNN model to classify the synthetic and real im- ages in their corresponding diseases in this study. In an attempt to train and evaluate the CNN on a comprehensive dataset that comprises conversations from recognised Language Forums, we measured the "metrics such as accuracy, precision, recall and F1-score to assess the performance of the CNN" similar to [20]

CNN Model Architecture: Our CNN model is designed as a sequential architecture, consisting of multiple convo- lutional and "pooling layers, followed by fully connected layers." The model structure is as follows:

1) Input Layer: Accepts images of size 128x128 pixels with 3 color channels (RGB).
2) Convolutional Layers:
– 1st layer: 32 filters with a "3x3 kernel", using "ReLU activation".
– 2nd layer: 64 filters with a "3x3 kernel", using "ReLU activation"
– 3rd layer: 64 filters with a "3x3 kernel", using "ReLU activation"
3) Max Pooling Layers: At each convolutional layer, the spatial dimension is downsampled in both axes with a 2x2 max pooling operation.
4) Flatten Layer: Transforms the 3D feature maps into a 1D feature vector.
5) Dense Layers:
– First dense layer: 128 neurons with ReLU acti- vation.
– Dropout layer: In order to prevent overfitting, 50% dropout rate was used.
– Output layer: Setting softmax activation for mul- tiple class classification or equal number of neu- rons.

Using Adam optimizer with a learning rate fixed to 0.001 and categorical cross entropy as the loss function, model is compiled.

Training Process: We train the model using a custom data generator with various data augmentation techniques, as we rotate, change the brightness, shift width and height, apply shear transformation, and crop horizontal.

To optimize training process, we employ learning rate reduction strategies and early stopping strategies. It uses the EarlyStopping callback which will stop training no later than 10 epochs if there is no improvement in vali- dation loss then it will stop training. ReduceLROnPlateau callback is used for reducing the learning rate when the validation loss starts plateauing, so we can fine tune the model's parameters.

Evaluation and Visualization:

1) Accuracy and Loss: We plot the training and val- idation accuracy and loss over epochs to visualize the model's learning progress.
2) Confusion Matrix: To see where the model fails, a class wise confusion matrix is made so we can see the biases and errors in this.

CNN for detecting Brain Tumour: For the detection of brain tumors, we applied our CNN model to a com- prehensive dataset comprising both real and synthetic MRI images greatly inspired from [1]. The real im- ages were sourced from the Brain Tumor MRI Dataset, which includes "7,023 human brain MRI scans" classified into four categories: "glioma, meningioma, no tumor, and pituitary". To augment this dataset and improve the model's capabilities, we incorporated the synthetic images generated by our previously trained GAN model. The combined dataset provided a rich and diverse set of brain MRI scans, enhancing the CNN's ability to learn and distinguish between different tumor types and healthy brain tissue. We used 5,712 images from the original dataset for training, supplemented by the GAN-generated synthetic images. This method not only increased the amount of training data but also enhanced the model's robustness by presenting it with a broader range of image features. The CNN was then trained on this augmented dataset, leveraging the power of both real and synthetic medical images to enhance its accuracy in detecting and classifying brain tumors.

Below is the visualization of the training and validation accuracy and loss of the CNN model per epochs to help us see the model's performance.

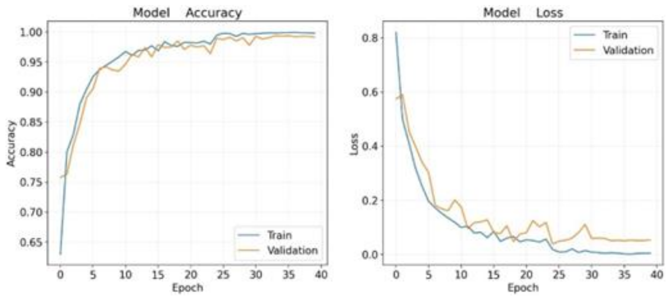

Fig. 3. Model accuracy and loss per epochs

We also generated a confusion matrix to give the break- down of true positives, false positives, true negatives, false negatives per class and give a general view of how much accurate the model is.

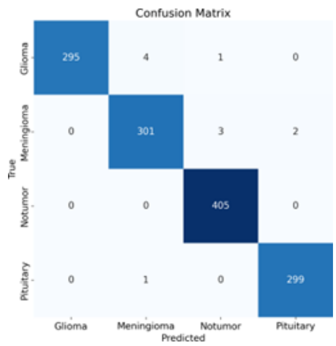

Fig. 4. Confusion Matrix

Finally, we show that our CNN model trained on a mixture of real and GAN generated synthetic brain MRI images show high performance for classifying brain tumors into multiple categories. Not only did this approach use the power of Deep Learning for medical image analysis, but it demonstrated the benefit of synthetic data in improving the accuracy of diagnostic in neurological imaging.

Explainable AI

We integrate "Gradient-weighted Class Activation Mapping (Grad-CAM)" as an "explainable AI" technique to help in- crease the interpretability and transparency of our CNN model for brain tumor detection. Grad-CAM shows us the most important part of the image that enables the model to make that specific prediction. The technique uses this gradient flow, over the final convolutional layer of the CNN, to generate localization maps that are class discriminative. Implementing Grad-CAM is our bridge that bridges the gap between the model's high accuracy and its interpretability, whereby med- ical professionals could understand and trust what the model does. The Grad-CAM visualizations provide invaluable clues as to which parts of the brain MRI scans are most important to tumor detection and classification, and could contribute to more precise diagnoses and better tumor treatment planning. We design our Grad-CAM model to explain our CNN model's predictions on brain tumor MRI images. Grad-CAM generates class discriminating localization maps that identify the image regions most responsible for making a given classi- fication. Specifically, for our implementation of GradCAM, we first load and preprocess the input image, we make predictions using the CNN model and finally we compute the gradients of the top predicted class for the input image. Next we extract the importance weights from the gradients and use them to normalize the channels input to the convolutional layer to produce a heatmap where each region in the input image is assigned an importance weight. Finally, the heatmap is superimposed over the actual image to show in a clear visual representation what the model has decided. When you run Grad-Cam on our CNN model.

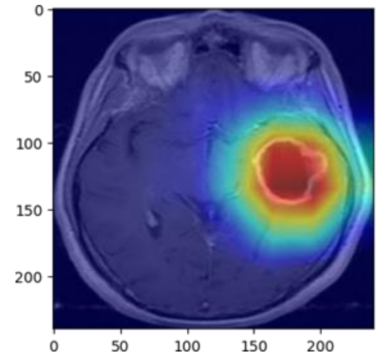

Fig. 5. Grad-CAM Heatmap of Glioma Tumor

In the above figure 5, "Grad-CAM heatmap superimposd" on original image with the regions that contribute most to model's classification of tumor as glioma highlighted.

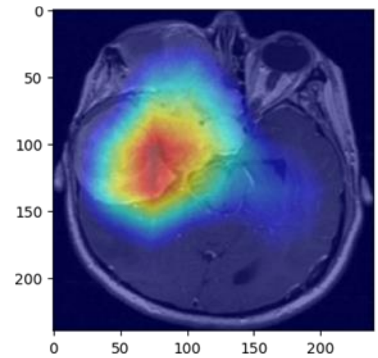

Fig. 6. Grad-CAM Heatmap of Meningioma Tumor

Similarly in the above figure 6, "Grad-CAM heatmap" on original image shows the regions which the model relied upon while classifying the tumor as meningioma.

Like wise we can generate Grad CAM heat maps for one more two classes notumor and pituitary using same approach itself. Using the Grad-CAM technique to the CNN model's prediction on these classes, we are able to visualize the regions of input images that is most influential in the model's classification decisions. This allows us to learn more about how the model makes a decision for each of these four classes (glioma, meningioma, notumor, and pituitary). Finally, these Grad-CAM heatmaps conditioned on the predictions of the model reveal the best performing regions of the image to the model and can be used to further refine the model's performance.

IV. Conclusion

Finally, we integrate GAN based data augmentation and CNN based image classification with XAI techniques, to create the first comprehensive and also creative approach to the detec- tion of deadly diseases from medical images. We achieved high accuracy over different disease categories through synthetic image augmentation of existing datasets and use of CNN models for classification, including brain tumors and it's classes. Further integration to Grad-CAM helped further the model's interpretability and transparency to clinician value, yielding insights into how the model made its decisions. This research paves the way toward more reliable, interpretable AI driven diagnostic systems and improves patient outcomes in the healthcare sector.

Secondly, the core principles of our approach can be eas- ily adapted to detect more deadly diseases, including lung and breast and prostate cancer, for example, by training the models on the corresponding medical image datasets. Our versatility suggests that this framework is broadly applicable to computer-aided diagnosis and disease detection.

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