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HYBRID ARCHITECTURE STRATEGIES FOR THE PREDICTION OF ACUTE PULMONARY EMBOLISM FROM COMPUTED TOMOGRAPHY IMAGES

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Abstract. The timely identification of pulmonary embolism is of utmost importance, as the condition has the potential to be life-threatening if not promptly addressed. The assessment of the severity of a pulmonary embolism (PE) frequently necessitates a time-consuming and potentially life-threatening estimation by a medical practitioner. The primary objective of the study was to investigate the potential utility of an artificial neural network in assisting physicians with the identification and prediction of pulmonary embolism risk in patients. Deep learning algorithms are frequently employed in medical imaging to enhance image analysis due to their ability to automatically learn representations from large datasets, as opposed to relying on pre-programmed instructions . The implementation of automated systems has the potential to decrease the level of physical effort needed and enhance the efficiency of diagnostic procedures for medical professionals. Efficient training and calculation processes are crucial for the proper execution of the implementation. The Tensor Processing Units (TPUs) developed by Google are employed to expedite the process of training., with the computational tasks being executed through Google Colab, a platform offered by Google Cloud TPUs. In order to achieve outcomes comparable to human judgment, deep learning algorithms engage in reasonable assessments of data based on a predetermined logical framework. Diagnosing pulmonary embolism (PE), a potentially lethal yet curable condition, poses challenges in early detection. A distinctive convolutional neural network (CNN) model was developed and examined for the purpose of distinguishing between pulmonary embolism (PE) and computed tomography (CT) pictures.

The proposed study yields a precision rate of 91.2%, showcasing an enhancement compared to current convolutional neural network (CNN) architectures that include limited trainable parameters. Furthermore, our model provides interpretability by the utilization of computed tomography (CT) images, specifically in the inferno and bone models. Our proposed deep learning model has the potential to predict the presence of PE and other associated features in current cases.

Key words: Deep Learning, Pulmonary Embolism, Dense Net, CT Scan, Artificial Intelligence

1. Introduction. Machine learning is a constituent part of both artificial intelligence (AI) and machine learning itself, and conversely, AI and machine learning encompass machine learning as a subset. Artificial intelligence (AI)[1], a broad concept, pertains to computer programs that exhibit human-like behavior. The advent of machine learning, which encompasses a variety of algorithms[2,3], has facilitated the realization of these achievements. Machine learning is a subfield that falls under the domains of both artificial intelligence (AI) and machine learning itself, and conversely, AI and machine learning encompass machine learning as a subset. Artificial intelligence (AI), a broad concept, pertains to computer programs that exhibit human-like behavior. The advent of machine learning, which encompasses a range of algorithms, has facilitated the achievement of these outcomes.

Deep Learning, on the other hand, is a subset of machine learning that is inspired by how the human brain is structured [4,5]. In order to analyse data and come to conclusions that are comparable to those of humans, deep learning algorithms employ a predetermined logical structure. Deep learning with neural networks is used to achieve this [6,7]. The basic diagram of deep learning is as shown in Fig.1.1. and the neural network is shown in Fig.1.2.

Deep learning algorithms are constructed dynamically to work across many layers of neural networks and are nothing more than a collection of previously trained decision-making networks. Then, each of these is put through a series of simple layered representations before moving on to the next layer [8].

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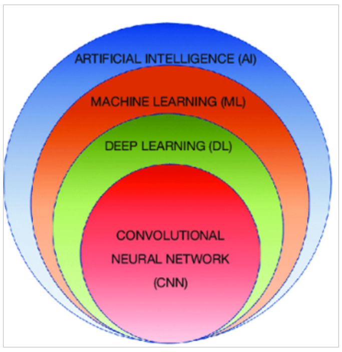

Fig. 1.1: Deep Learning ref [2]

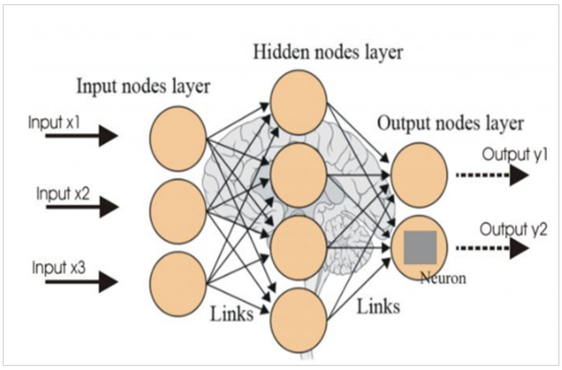

Fig. 1.2: Neural Network of ref [4]

The principal benefit of deep convolutional neural networks (DCNNs) illustrated in Fig.1.3 lies in its hierarchical architecture, which is distinguished by several layers. A three-dimensional neural network design, known as a deep convolutional neural network (DCNN), is utilized to concurrently process the Red, Green, and Blue components of an image [9,10]. The application of this methodology results in a substantial reduction in the number of artificial neurons required for image processing, as compared to traditional feed forward neural networks. Deep convolutional neural networks (CNNs) are a machine learning model specifically developed for the purpose of image processing and analysis [11,12]. These neural networks accept photos as input and employ them in the training process of a classifier. The network employs a unique mathematical operation called a "convolution" instead of doing matrix multiplication.

The accuracy of CNN classification in medical image analysis surpasses that of human visual perception, enabling the detection of anomalies in X-ray or CT scan pictures. These systems possess the capability to examine sequences of images, such as those obtained over an extended duration, and detect small variations that may elude human analysts. Additionally, this enables the execution of predictive analyses. The training of classification models for medical pictures is conducted using extensive public health datasets. The resultant models possess the capability to be applied to patient test outcomes[13], enabling the identification of medical disorders and the automated generation of a prognosis.

PE refers to a group of conditions that cause scarring in the lungs. Diffuse parenchymal lung diseases is another term for it. Scarring causes the lungs to stiffen, making breathing and absorbing oxygen more difficult. PEs cause permanent lung damage that worsens with time and shown in Fig.1.4.

1.1. Pulmonary Embolism Types:.

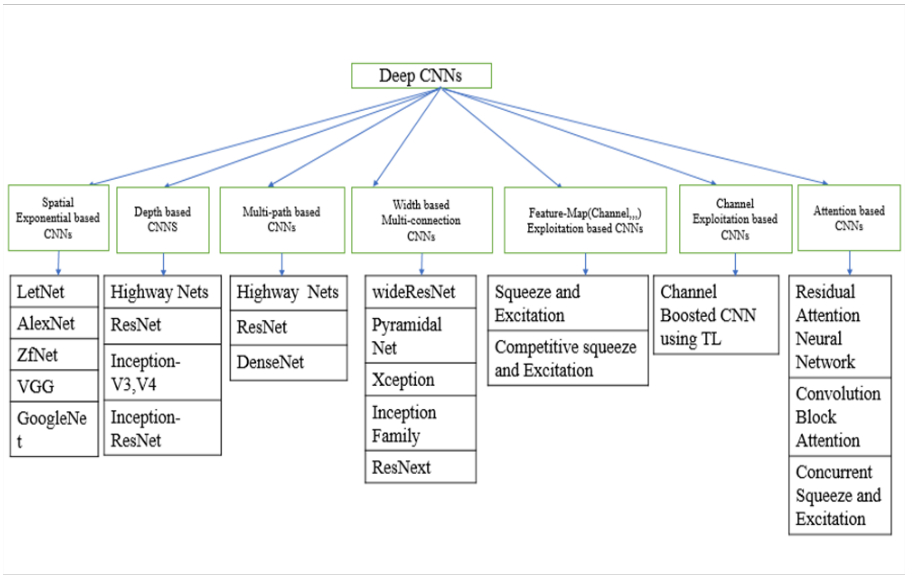

Fig. 1.3: Types of Deep Learning Algorithms

Fig. 1.4: Lung effected with PE of ref [8]

1. Acute pulmonary embolism: Acute pulmonary embolism is a condition where blood clots develop in the pulmonary arteries and block them, making breathing extremely difficult and causing chest pain.
2. Chronic pulmonary embolism: Multiple blood clots and repeated pulmonary embolism caused by 'deep vein thrombosis' do not dissolve and continue to obstruct the blood supply to the lungs, resulting in chronic pulmonary embolism.

2. Literature Survey. In the study conducted by the author, a number of machine learning models were developed and employed, including neural networks, gradient boosted trees, and logistic regression [14]. The author provided training to the participants using a dataset consisting of health information from 63,798 inpatients who received medical and surgical care at a prominent medical center in the United States. The XGBoost model had superior performance in predicting pulmonary embolisms. The XGBoost model achieved an AUROC of 0.85, demonstrating a sensitivity of 81% and a specificity of 70%.

The neural network model proposed by the author in reference [15] incorporates the InceptionResNet and CNN architectures, together with a long-short-term memory network, to effectively process whole stacks of CTPA images in the form of sequential slices. The analysis of the model's efficiency was conducted by considering multiple parameters. The author's conclusion is that, at the stack and slice levels, both models demonstrated strong performance, with specificity and sensitivity rates of 93.5% and 86.6% respectively.

In the aforementioned scholarly article [16], the researcher conducted a comparative analysis of two variants of Artificial Neural Networks (ANNs). The study was conducted utilizing 294 patients from three hospitals, employing feed-forward and Elman backpropagation models. The researchers utilized an enhanced artificial neural network in conjunction with a perfusion scan diagnostic technique. The study achieved accuracy rates of 93.23% and 86.61% for the relevant tasks. This study has the potential to enhance the accuracy of risk assessment for patients and contribute to reducing mortality rates, benefiting physicians, medical assistants, and healthcare professionals. The author utilized four pre-existing convolutional neural network (CNN) architectures, namely Inception, VGG-16, ResNet50, and Mobilenet, in order to classify cases of pulmonary embolism, as stated in reference [17]. The experimental results indicate that the Inception-based CNN model exhibits superior performance compared to other CNN architectures.

The study described in Reference [18] proposes a systematic approach for the identification of pulmonary embolisms through the utilization of computed tomography (CT) scans. The U-net network is employed to identify potential embolism candidates and afterwards conduct classification. The approach achieved a Dice coefficient of 0.81 and an Intersection over Union (IoU) score of 0.79. The author [19] compared pretrained design performance. This comparison uses loss, accuracy, and AUC. The study found that slimmer architectures including MobileNet, VGG, ResNet, and U-net outperformed Inception, DenseNet, and Xception. This study also found a significant confidence gap between picture and exam features.

The author [20] presented a novel approach in their study, which aimed to predict outcomes on computed tomography (CT) exams. The methodology employed in this study consisted of implementing a two-stage model that integrated Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The technique that was advised shown a higher level of performance in comparison to both the conventional CNN model and a single stage CNN-LSTM network. This is supported by the Area Under the Curve (AUC) value of 0.95.

The study by [21] presents a mask RCNN model that utilizes a probability-based approach to enhance the local properties of densely populated microscopic particles by initially upsampling the values in the feature map. Additionally, a specific region was selected from the retrieved image based on the probability of pulmonary embolism (PE) occurrence. The extraction of anchors within the candidate zone, as opposed to the entire image, offers time and space efficiency benefits, particularly in light of the expanding feature maps. The author asserts that the quality of the work was enhanced with the elimination of a majority of invalid anchors. The empirical evidence demonstrates that the proposed technique is both effective and efficient.

In [22], the author used an artery-aware 3D fully convolutional network (AANet) to encode arterial data as prior information to recognize arteries and PEs. The author suggests using local and global vascular artery values as soft attentions to distinguish pulmonary embolisms (PEs) from other soft tissues. The CAD-PE dataset was used to test the techniques for the artery.

3. Proposed Model. A collection of Chest CT-Scan images was acquired for our investigation using the Kaggle platform. The collection comprises chest computed tomography scans and associated patient medical data. The dataset has two subfolders. The folders serve as repositories for training and examination materials. The existing data was further adjusted in order to consolidate the final training data by reducing the potential influence of confounding variables and enhancing the distribution of classes. Furthermore, we have been provided with the CSV files containing the train and test datasets. The train folder consists of CT scans from a sample of 100 distinct patients, whereas the test folder exclusively comprises CT scans from a smaller sample of only five patients. In order to optimize the model's ability to create data with a high level of accuracy and efficiency, it is recommended to utilize the train folder and is shown in Fig.3.1.

One of the parameters is frequently given more weight by deep learning algorithms. These two objectives can coexist using Pytorch, a machine learning library that makes it possible to use code as a model, makes debugging easier, and is compatible with a variety of widely used computing libraries while still being effective and GPU-friendly.

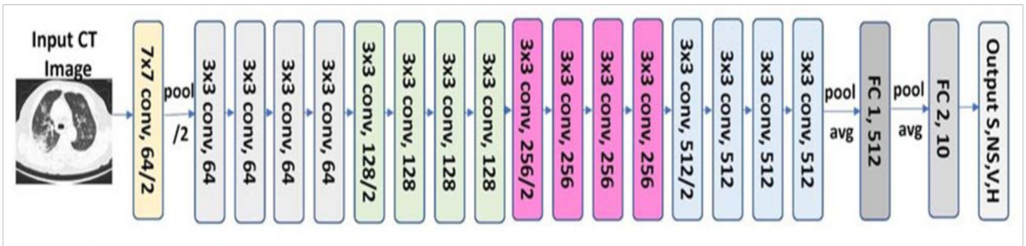

Fig. 3.1: ResNet Architecture

3.1. Transfer Learning Techniques:. A substantial dataset and robust computer resources are necessary to develop a high-performing CNN from the beginning. Here's where TL comes in; it's a super-effective strategy that drastically cuts training time while still needing some information [23, 24]. The goal of this approach is to use crucial information (weights) from CNN models that have already been trained on a big dataset to address problems in other domains. TL improves CNN models' generalization abilities. This has led to many uses for pre-trained CNN models' TL, especially in the medical imaging field, where it can aid in the classification of pictures used in diagnostic procedures. Several widely used CNN models have already been pre-trained. We have utilized ResNet and DenseNet models to differentiate between PE and not PE because of their high performance in picture classification. To begin, we collected 644 CTA photos from both PE and non-PE classrooms to create a well-rounded collection. Then, we've used a method called data augmentation to further enrich the dataset by adding in updated versions of the original input images.Operations like as rotation, resizing, cropping, and zooming have been used. The developed dataset was actually used to feed the already-trained ResNet and DenseNet CNN models.

3.2. RESNET Architecture:. The ResNet, also known as the residual neural network, is a type of architectural design that integrates residual learning into a conventional convolutional neural network. This integration serves as a strategy to address the issues of gradient dispersion and accuracy degradation that are commonly observed in deep networks throughout the training process [25]. The user possesses full control over the accuracy and speed of their development. The methodology for implementing the ResNet model is illustrated in Figure 3. Assume that the variable x represents the input value. If the working weights exhibit negative values, it is advisable to disregard such data. The weights are exclusively accessible to the relu activation function, which lacks the capability to transmit them to other entities.

Dense Net was created because the vanishing gradient has a major impact on the performance of advanced neural networks. In other words, the further apart the input and output levels are, the more likely it is that the information will be lost along the way. The output of the first layer is the input to the second layer whenever the composite function is utilized. Implementation details of the Dense Net model are depicted below. This multi-step method incorporates non-linear activation layers, convolution, pooling, and batch normalization. DenseNet-121 is one of the several Dense Net representations available and is an implementation of the Dense Net Figure format. DenseNet provides three distinct Dense Blocks, with DenseNet-160 and DenseNet-201 being the most popular options. The numbers signify the neural network's layer count. Numbers are $5 + (6 + 12 + 24 + 16) * 2 = 121$. Compact Net Convolution and pooling at Layer 5 Transitional Layers: 3 (6,12,24) Classification is the top layer (6) Block 2 ($Conv1*1and3*3$). The vanishing gradients issue is resolved by dense networks, allowing for the training of models with fewer parameters. Data moves swiftly as a result of dynamic feature propagation. In the Figure below , there are three dense blocks that make up a deep dense net. Convolution and pooling are used to change feature- map sizes and link two nearby blocks.

Densely Connected Convolutional Network, also referred to as DenseNet, is an alternative nomenclature for this particular network architecture. The concept of having dense blocks in a neural network architecture, where each layer is interconnected with every other layer in a forward feed way, serves several purposes. Firstly, it addresses the issue of vanishing gradient, which is a common challenge in deep learning. Secondly, it enhances the propagation of features throughout the network, allowing for more effective information flow. Lastly, it

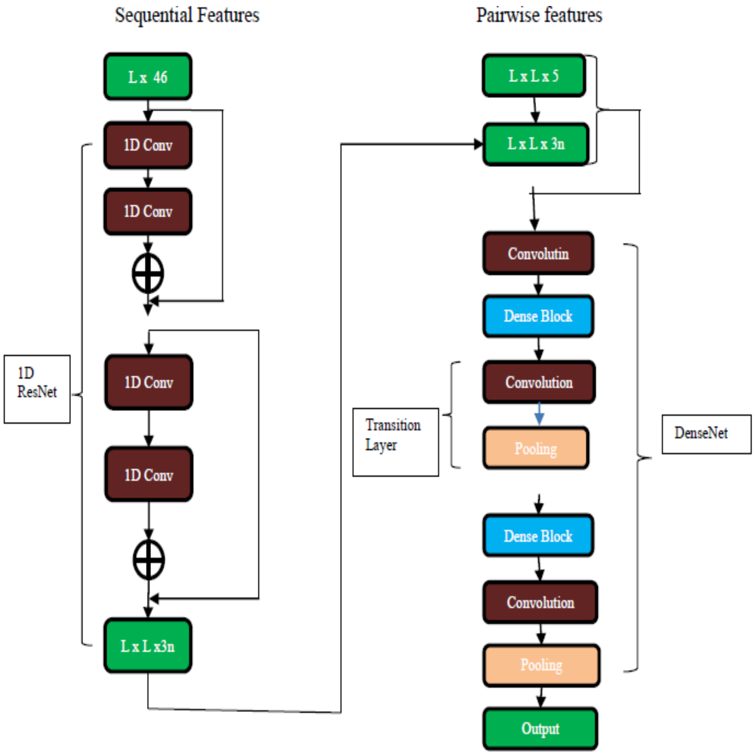

Fig. 3.2: Program flow

promotes the reuse of features, enabling the network to leverage previously learned.

To incorporate residual learning into a DenseNet architecture, original DenseNet design is modified by adding residual connections. Here are the various steps which are involved in the proposed model:

Dense Block. The dense block is the basic building block of DenseNet, consisting of multiple consecutive layers. In each layer, the output feature maps are concatenated with the input feature maps from previous layers.

Transition Layer. After each dense block, a transition layer can be added to downsample the spatial dimensions of the feature maps. This typically involves a convolutional layer and a pooling operation, such as average pooling.

Residual Connection. Skip connections are introduced within the dense block or between the dense blocks. These skip connections can be implemented by adding the input feature maps to the output feature maps of a dense block or a transition layer.

Global Average Pooling and Classifier. At the end of the network, apply global average pooling to aggregate the spatial information into a single feature vector. Connect this feature vector to a fully connected layer or a softmax classifier for the final prediction. By combining the dense connections of DenseNet with residual connections, we can benefit from both the feature reuse and gradient flow properties of DenseNet and the ease of training and optimization provided by residual learning.

This modified architecture, often referred to as DenseNet with residual connections, can improve the model's expressiveness, training efficiency, and overall performance on various tasks.

The framework utilized in this study is founded upon an integrated deep neural network, as depicted in Fig. 3.2. This network is comprised of one-dimensional residual and densely connected convolutional networks. The ResNet architecture possesses the ability to address the issues of gradient vanishing and exploding by virtue of its distinctive identity and residual mapping properties, hence enabling effective training of deep network structures. However, it is important to note that the number of parameters in ResNet is directly related to its

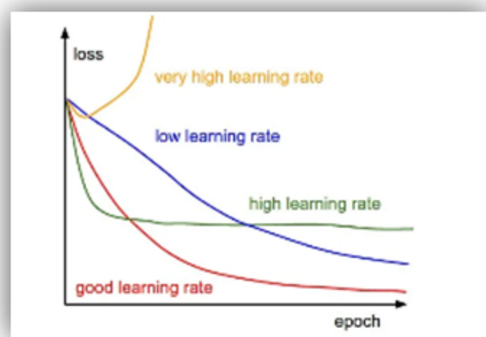

Fig. 3.3: Learning Rate

depth. The DenseNet architecture addresses the issue of gradient vanishing by leveraging its dense connections, which facilitate optimal feature reuse and enhance feature transfer. During the data preparation phase of our system, one-dimensional sequential features are encoded as vectors and subsequently inputted into the ResNet network. Subsequently, the two-dimensional pairwise data are integrated with the one-dimensional characteristics obtained from a one-dimensional residual network, and the combined features are then fed into the DenseNet network.

To incorporate several input features for a residue pair, we concatenate the vectors representing the residues and their corresponding features, namely $=v_1, v_2, ., v_i, ., v_L$. This concatenated vector is then utilized as a single input feature for the residue pair. Next, the pairwise characteristics are integrated with the aforementioned elements to construct the input for the subsequent section of the network. In order to mitigate the issue of overfitting in the network, a dropout method is employed, whereby neurons are randomly deactivated during the training process at a dropout ratio of 80%. An efficient stochastic optimization technique was employed in this study, utilizing the Adam optimization algorithm with a learning rate of 0.01. In our proposed model, the training of model parameters is accomplished through the utilization of the maximum likelihood function. The loss function, which is employed to quantify the discrepancy between predicted and actual values, is formulated as the negative log-likelihood function, specifically referred to as the cross-entropy function. The formula is as follows:

$$E(t, y) = -\sum_i t_i log Y_i \tag{3.1}$$

3.3. Learning Rate:. The learning rate parameter, often ranging from 0 to 1, plays a crucial role in facilitating gradient updating. While its value is often modest, it can reach a maximum of 1 (equivalent to 100%). The attainment of the precise optimum of the loss function can be achieved by modifying the learning rate. Both low and high learning rates lead to inefficiency in terms of time and resource utilization [26,27]. A decrease in the learning rate leads to an extended duration of training, which subsequently results in escalated expenses for cloud GPU usage.A higher rate of occurrence could potentially lead to a model that lacks the ability to reliably forecast outcomes shown in Fig.3.3.

When there is a greater weight disparity between iterations, larger steps are taken [28,29]. The optimal outcome can be quickly attained using this method, but the precise optimal value cannot be. Every iteration is thought of as having smaller steps when the weight differences are smaller. In this method, more epochs are required to achieve the ideal result, but there are very few opportunities to miss the precise optimal value.

4. Results and Discussion. Rapid computation and training are needed for the implementation. Google Tensor Processing Units (TPUs) are employed to speed up training, while Kaggle Cloud TPUs are used to

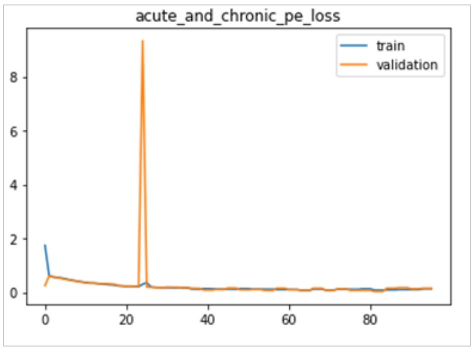

Fig. 4.1: Central PE Loss Of the system

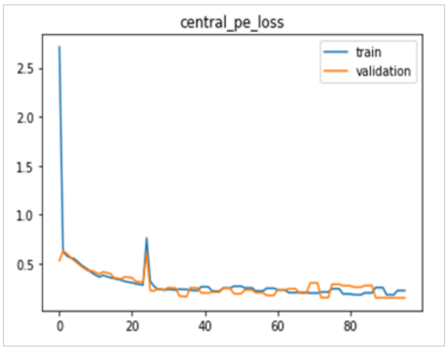

Fig. 4.2: Central PE Loss of the system

complete the work. Using a common training dataset with a batch size of 100 images and an initial learning rate of 0.000010, the PE- DeepNet model was trained across 25 iterations. The optimizer algorithm Adam was utilised, and the loss function was binary cross entropy. The model has a total of 4,399,489 parameters, 4,374,705 of which were trainable, and 24,784 of which were not. Under these circumstances, the model's training accuracy was 94.20 percent and its validation accuracy was 92.30 percent. The following figures show various loses of proposed model

The evaluation or quantification of a model's performance depends in detecting or diagnosing central pulmonary embolism (PE) and Intermediate Pulmonary Embolism. The central PE loss and Intermediate PE loss and acurracy graphs are depicted in Fig.4.1 and Fig.4.2 respectively.

The suggested model's loss and accuracy plots are displayed in the figures above. The validation loss can be lowered to 0.423 by using a higher number of epochs. Area Under Curve of the RoC is 0.567691, Accuracy is 91.2 percent , and Train Loss is 0.513 for the proposed architecture whereas. after 30 epochs, ResNet is 81.54 percent accurate, and the AUC value is found to be 0.853 and training and validation loss are found to be 0.6112 and 0.548 respectively shown in Fig.4.3. Similarly for the same number of epochs for DenseNet we have 83.78 percent accuracy,AUC value is around 0.866 and the training and validation losses are found to be 0.5676 and 0,477 repectively and all the obtained results are depicted in Table. 4.1.

Fig.4.4 is an inferno-themed colormap of CT scans of patients. From the subclass ”Perceptually Uniform Sequential,” a spectacular visual depiction of the ”inferno” is at your disposal shown in Fig.4.5. One of the matplotlib color maps, ”The Luminance of Inferno,climbs smoothly and uniformly in brightness over time. The body is black, yet there are attractive purple overtones shown in Fig.4.6.

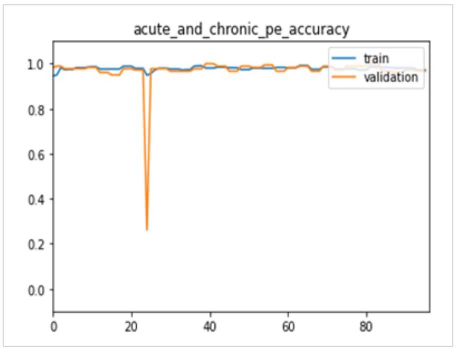

Fig. 4.3: PE Loss and accuracy

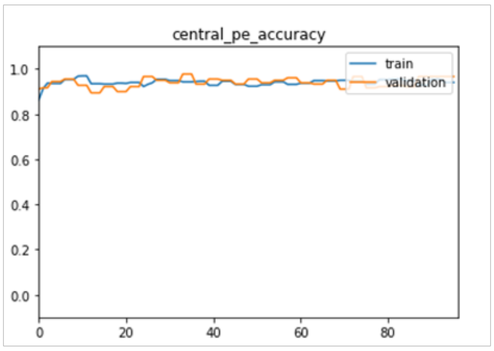

Fig. 4.4: Intermediate PE Loss and accuracy

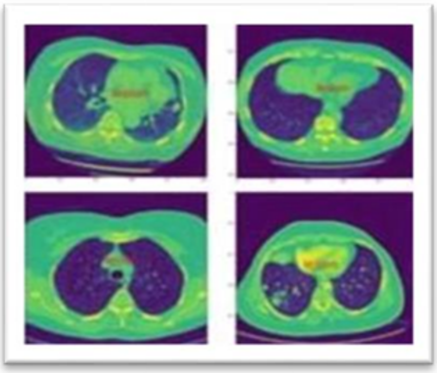

Fig. 4.5: CT scans in Bone Model

5. Conclusion. By combining both ResNet and DenseNet we can leverage the strengths of both the architectures.This hybrid architecture aims to capture the benefits of residual connections in ResNet and dense connections in DenseNet, While we have different ways to combine these techniques ,we have introduced skip connections along with dense connections within the network so as to improve to the gradient flow ,feature reuse and overall performance. The proposed model was applied to the provided dataset to find the presence of Pulmonary Embolism and for calculation of Accuracy, and the associated validation loss. Using these results,

Table 4.1: Comparison Table

	AUC	Accuracy	Training loss	Validation Loss
ResNet	0.853	81.54	0.6112	0.548
DenseNet	0.866	83.78	0.5676	0.477
Proposed system	0.870	91.2	0.513	0.423

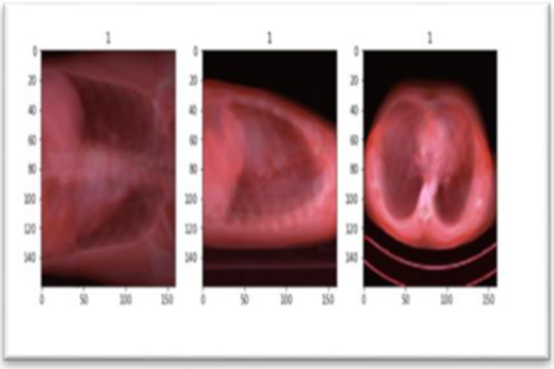

Fig. 4.6: CT scans in Inferno Model

we were able to predict a person's likelihood of having a disease, enabling an early diagnosis. A low validation loss number improves the model's performance. The model network's use of the ReLU activation function allowed it to focus on the most relevant information while ignoring the rest. The code is built in CUDA, a parallel computing environment and language that makes extensive use of the GPU to speed up calculations.

There are numerous restrictions and issues with deep learning technology, despite of its successes in the medical and therapeutic fields. When there is a large amount of annotated data, deep learning typically calls for analysis. This It's difficult to annotate medical records. Images. The specialised knowledge of radiologists is required for the labelling of medical images. Therefore, it takes time to annotate a suitable medical image. Moreover, it takes a lot of time. Medical image annotation is possible, but is currently impossible due to the sheer number of unlabeled medical images. Due to their extensive storage in PACS for a long time, there are a tremendous number of images. A considerable amount of time using Deep learning will be saved as an annotation if it can use unlabeled images and learning techniques.

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