Volume 9, Issue 6, June – 2024 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN332

Comparative Analysis of Deep Learning Models for Pneumonia Detection in Chest X-Ray Images

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Abstract:- This paper focused on Comparative Analysis of Deep Learning Models for Pneumonia Detection in Chest X-ray Image. Pneumonia is one of the illnesses which are associated with the lung's region, which can lead to a severe condition when not diagnose or detected at early stages. The ability of the disease to restrict the flow of oxygen getting into the bloodstream makes the disease more dangerous as a result of existence of virus, bacteria or Fungi in the lung. Hence leads to untimely death. Experimental AlexNet ANN, ResNet50 ANN and DenseNet 121 ANN algorithms were to distinguish and detect pneumonia from non-pneumonia patients using medical images with AlexNet with a total number of 1877 images for both pneumonia and non-pneumonia patients were used to train the alexnet algorithm and 805 images of both pneumonia and non-pneumonia images were used for testing, the dataset contained a balanced combination of both pneumonia images and non-pneumonia images. The following results were gotten from the experiments for both AlexNet ANN and ResNet50 ANN respectively: the accuracy was 0.877, Sensitivity 0.834, specificity 0.917, f1Score 0.866 and the AUC which was 0.93; 0.817, Sensitivity 0.720, specificity 0.910, f1Score 0.793 and the AUC which was 0.88 and 0.915, Sensitivity 0.837, specificity 0.990, f1Score 0.906 and the AUC which was 0.98 with the Accuracy, Sensitivity, specificity and AUC values. The three Scenarios on three ANN Architecture were observed. It was found that all the three models were able to distinguish and detect pneumonia accurately with no significant error.

Keywords:- *Pneumonia, ANN, Deep Learning, Medical Imaging, AlexNet, ResNet 50, DenseNet 121.*

I. INTRODUCTION

Pneumonia is one of the few sicknesses that is related with the lungs. It can influence both grown-up and kids, regardless of orientation and age [1] pneumonia can be brought about by infection, microorganisms or Parasites. Which will in general be serious relying upon the main driver [2]. As indicated by the middle for infectious prevention and counteraction (CDC) it was found that there are around 12.4 passing per hundred thousand populace which makes it a sickness risky and equipped for coming about into mortality [3]. There are a few techniques for recognizing pneumonia clinically, one of the best techniques is the clinical imaging strategies. This strategy manages the utilization of clinical imaging methods such has attractive reverberation imaging (MRI),Xray pictures (CXR) and processed tomography (CT). This imaging methods give an itemized construction of what is the deal with the lungs locale wherein radiologist are having the option to identify irregularities that could respect location of pneumonia through actual assessment. In any case, this strategy is certainly not a dependable technique for recognition in light of the fact that its tedious and it requires a radiologist with undeniable level insight to precisely distinguish patient with pneumonia from non-pneumonia patient consequently making the requirement for a programmed location and conclusion strategy that can precisely recognize the sicknesses particularly at beginning phases so speedy therapy can be regulated to fix the illnesses [4].

AI is a sub classification of man-made consciousness that can gain and recognize examples or grouping from text, voice, video and picture dataset without been expressly been customized [5-6]. AI calculations has extraordinary capacities of handling huge datasets which for the most part may be troublesome or monotonous for human to comprehend or process such has wellbeing related information, research facility result, clinical sensor information from different gadgets like electronic wellbeing records [7]. Fake brain networks are exceptional kinds of AI which can perceive and recognize abnormalities in clinical pictures using strategies such has feature extraction, move learning. This has also made grouping and location of clinical sickness considerably more effective and exact [8]. In this examination Fake brain network explicitly, profound learning will be utilized in identification and recognizing impacted pneumonia from non-pneumonia utilizing three profound learning engineering specifically Alexnet, Resnet50, and DenseNet121. The Objective of this task is to explore how well ANN could identify and recognize a pneumonia patient and a non-pneumonia patient, likewise to examine which of this profound learning design will be the best and proficient in the determination and location of this sickness by contrasting Resnet-50, DenseNet121 and Alexnet. Man-made reasoning has been of key significance in clinical determination which have assisted with further developing finding treatment of a few sicknesses. ANN calculations assume significant part in this, there have been a few works that have been done as such far comparable to determination of clinical sicknesses. Okeke Stephen et al proposed a convolutional brain organization (CNN) model created from the beginning to recognize pneumonia in chest X-beam pictures. As opposed to strategies depending exclusively on move learning or customary methods, the model is worked without any preparation, upgrading unwavering quality and interpretability in clinical imaging. Given the test of procuring adequate pneumonia information, different information expansion procedures were utilized to support approval and grouping precision, bringing about critical upgrades [9].Amit Kumar Jaiswal et al introduced a profound learning approach for identifying and pinpointing pneumonia in chest X-beam (CXR) pictures. The distinguishing proof model, is based on Cover RCNN, a profound brain network that joins worldwide and neighborhood highlights for exact division at the pixel level. To additional upgrade strength through critical changes to the preparation cycle and an extraordinary post-handling step that solidifies bouncing boxes from numerous models. The proposed distinguishing proof model exhibits predominant execution when assessed on a dataset of chest radiographs portraying potential pneumonia cases [10].

II. METHODOLOGY

The dataset was utilized to examine how well ANN could recognize and recognize a pneumonia patient and a non-pneumonia patient, likewise to research which of this profound learning design will be the best and productive in the determination and discovery of this illnesses. This was completed through three situations which were (I) pneumonia patient and a non-pneumonia patient utilizing AlexNet Profound learning Model. (ii) pneumonia patient and a non-pneumonia patientusing ResNet50 Profound learning Model. (iii) pneumonia patient and a non-pneumonia patient utilizing DenseNet121 Profound learning Model. A complete number of 2682 pictures were utilized for every situation which incorporates 1877 pictures pneumonia and a non-pneumonia for preparing and 805 pictures for testing. The pictures were gotten from a few patient of both pneumonia patient and a non-pneumonia patient. Table 1 and 2 show the number of stages of preparation and testing that was utilized for every one of the situations of the examination.

Table 1: Images for Each Experiment

Experiment	Dataset	Training	Testing
pneumoniavs non-pneumonia patient (AlexNet).	[19]	1877	805
pneumoniavs non-pneumonia patient (ResNet50).	[19]	1877	805
pneumoniavs non-pneumonia patient (DenseNet121).	[19]	1877	805

Table 2: Images after Augmentation used for the Experiment

Experiment	Dataset	Training	Testing
pneumoniavs non-pneumonia patient (AlexNet).	[19]	7508	805
pneumoniavs non-pneumonia patient (ResNet50).	[19]	7508	805
pneumoniavs non-pneumonia patient (DenseNet121).	[19]	7508	805

Table 3: Result Table for Scenario A

	Accuracy	Sensitivity	Specificity	F1 score	AUC
AlexNet	0.877	0.834	0.917	0.866	0.93

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/IJISRT24JUN332

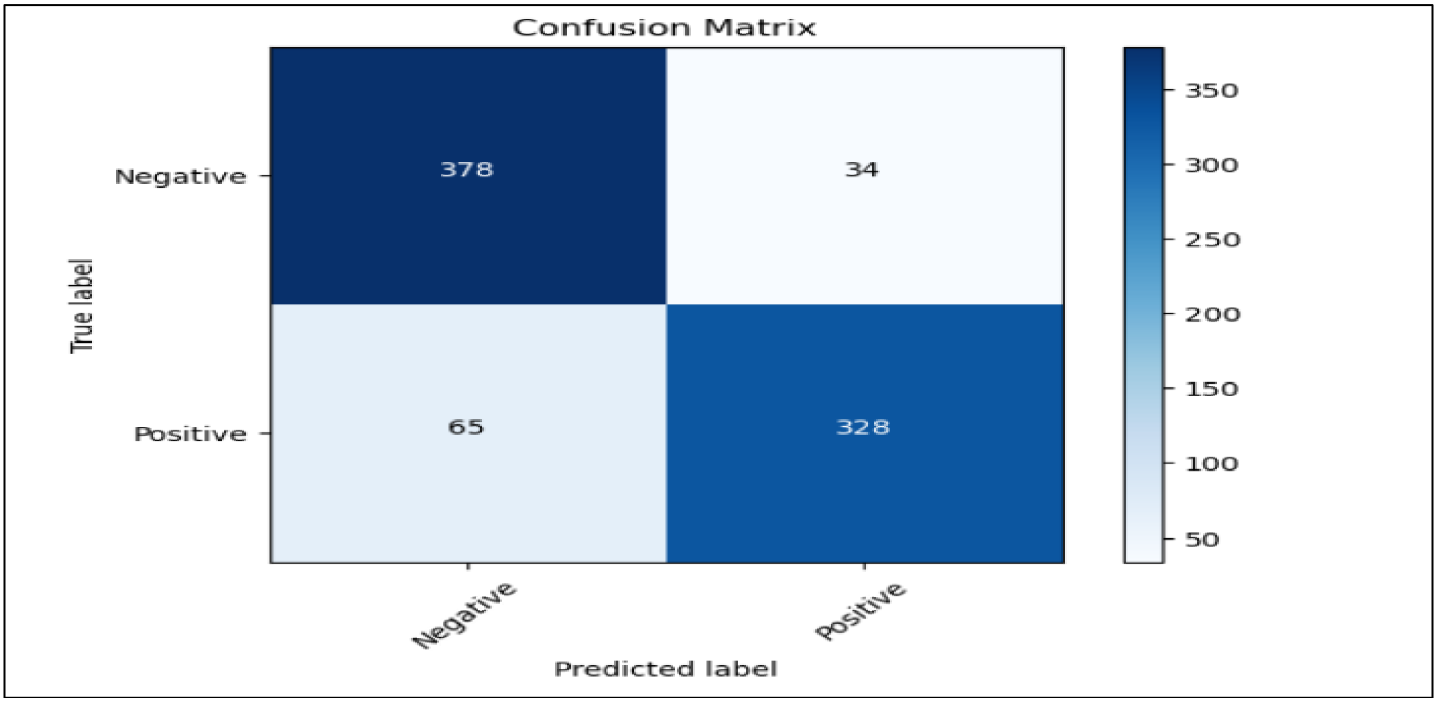

Fig 1: Confusion Matrix for Scenario A.

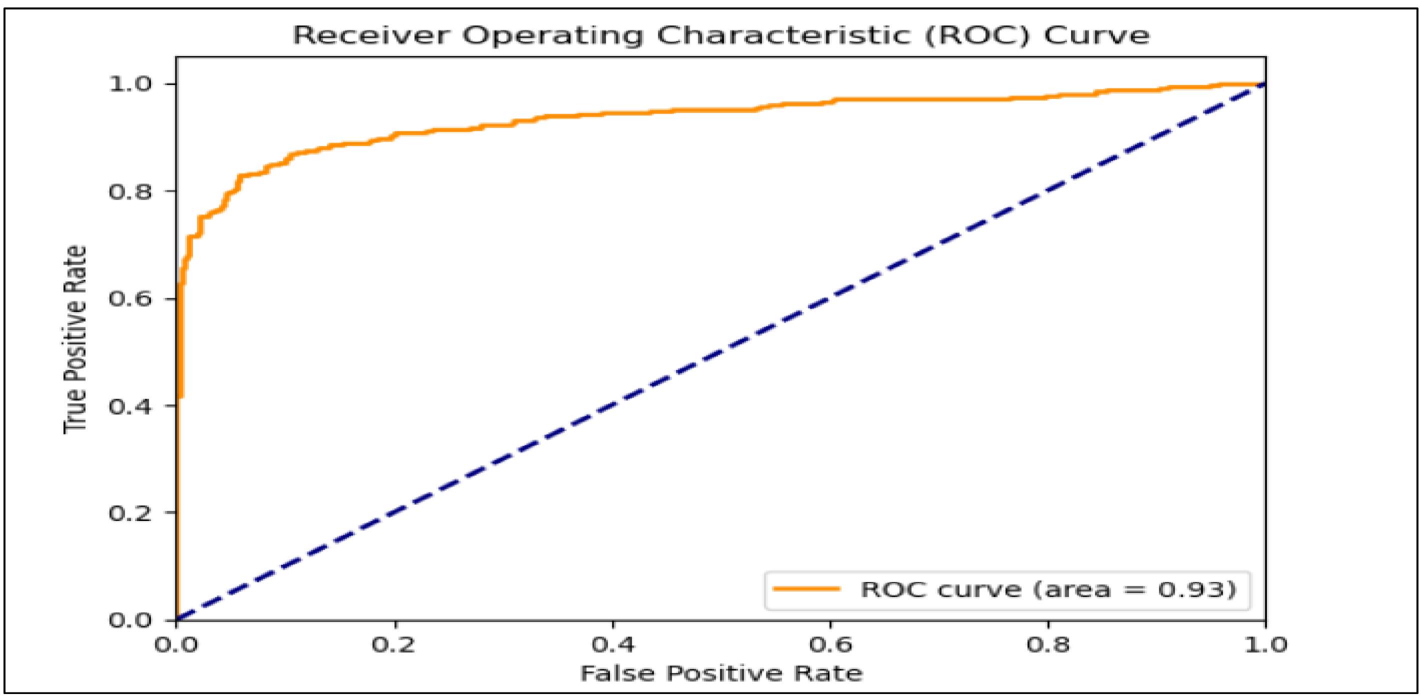

Fig 2: ROC Curve for Scenario A

Table 4: Result Table for Scenario B

	Accuracy	Sensitivity	Specificity	F1 score	AUC
ResNet 50	0.817	0.720	0.910	0.793	0.88

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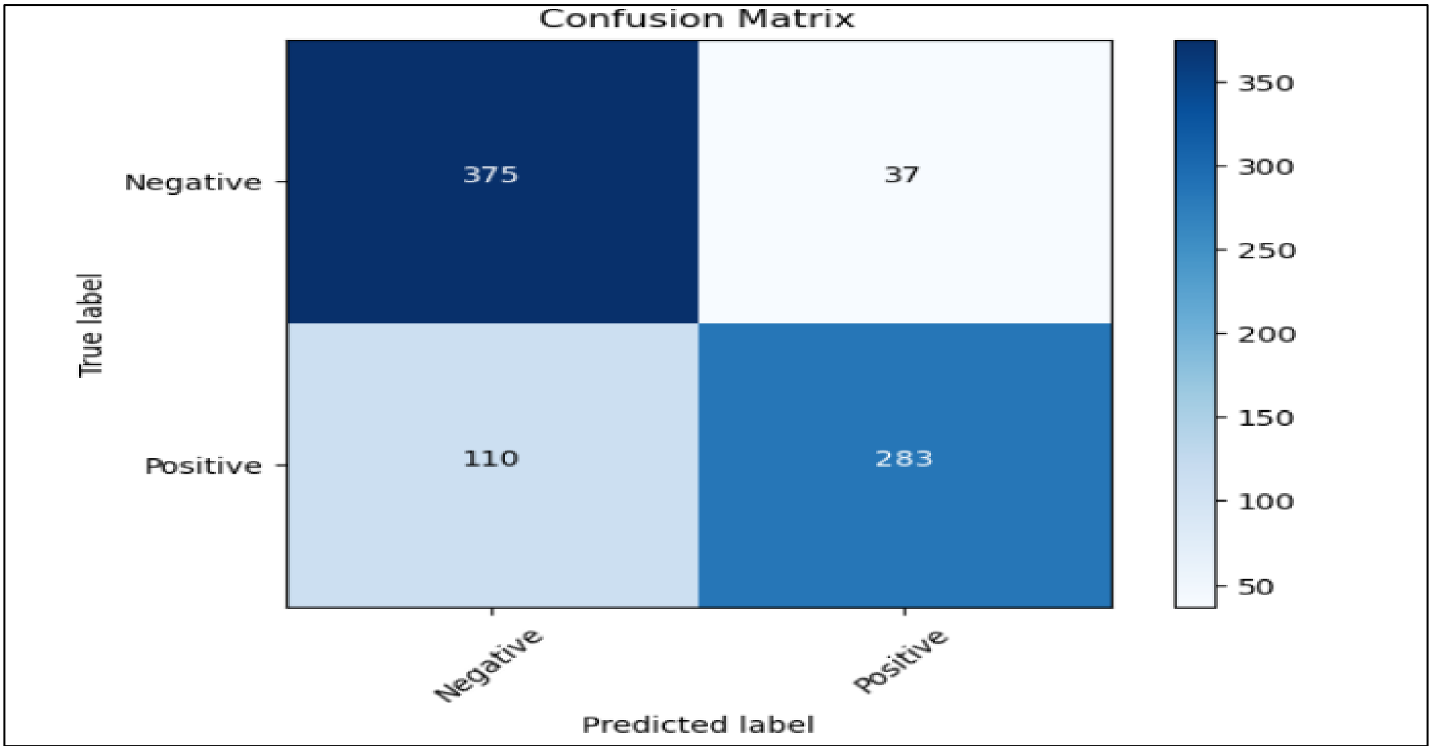

Fig 3: Confusion Matrix for Scenario B.

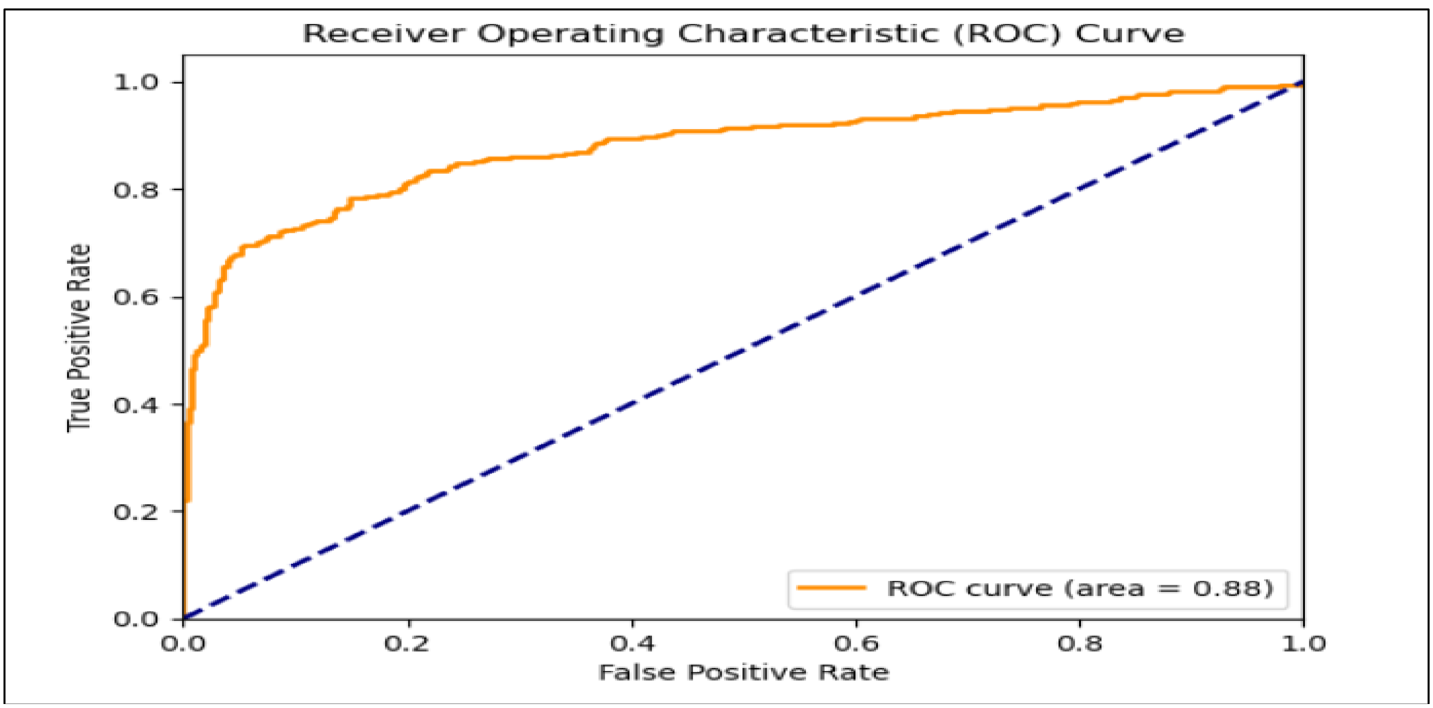

Fig 4: ROC curve for Scenario B.

Table 5: Result Table for Scenario C

	Accuracy	**Sensitivity**	**Specificity**	**F1 score**	**AUC**
DenseNet121	0.915	0.837	0.990	0.906	0.98

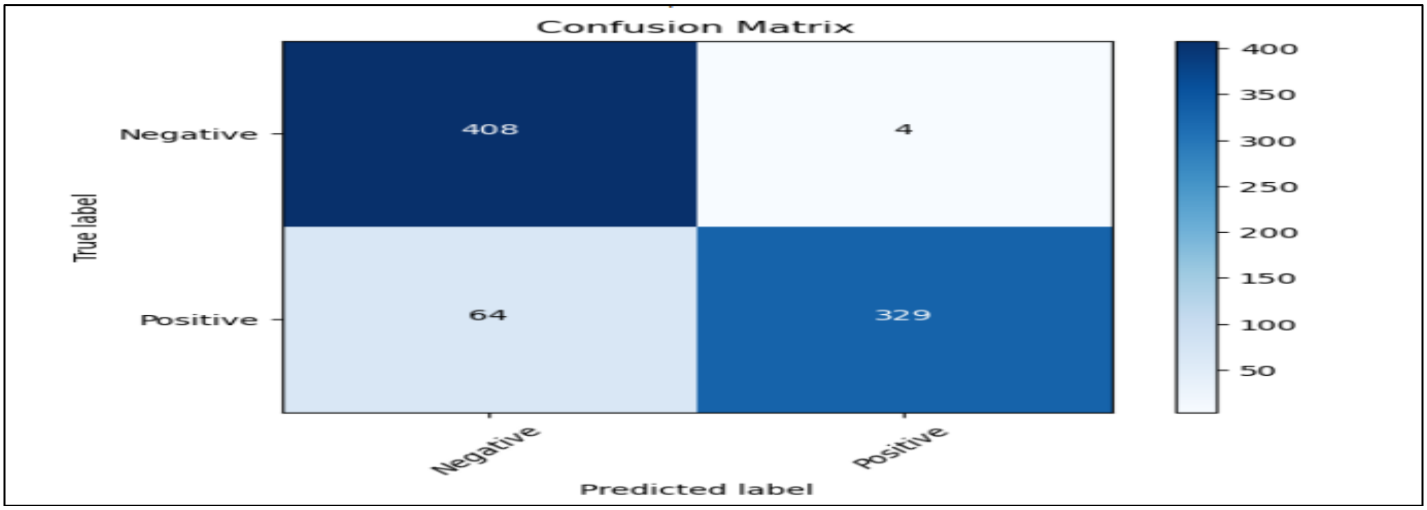

Fig 5: Confusion Matrix for Scenario C.

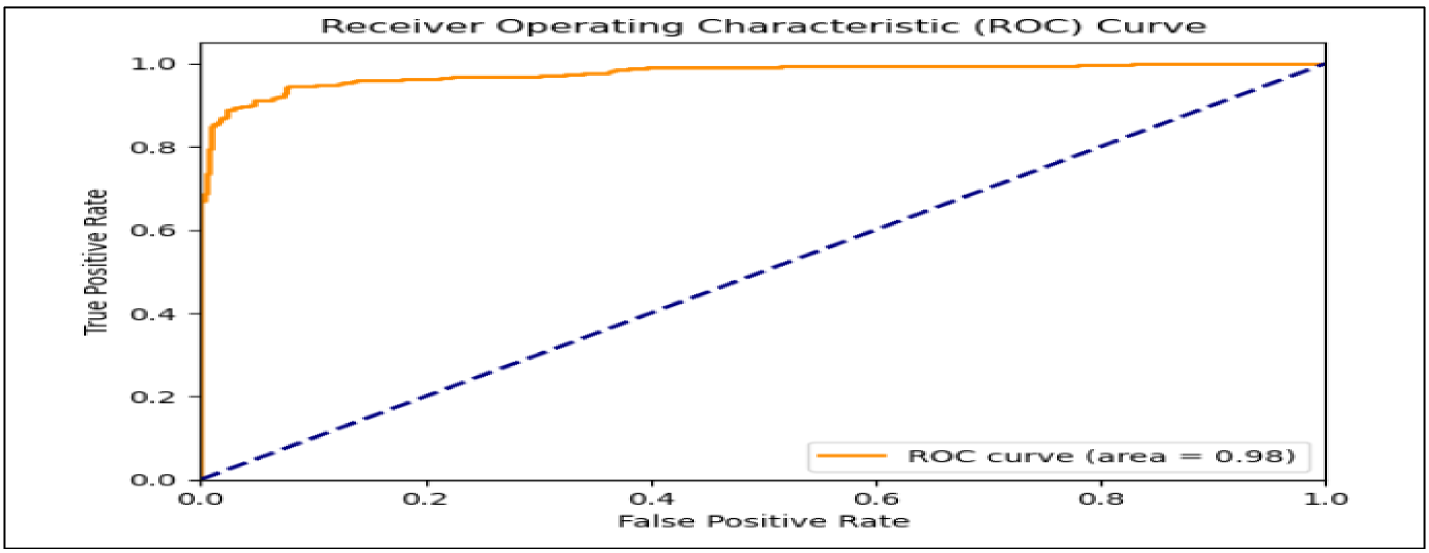

Fig 6: ROC Curve for Scenario C.

III. DISCUSSION

ANN was set to identify and recognize a pneumonia patient and a non-pneumonia patient, likewise to explore which of this profound learning design will be the best and productive in the diagnosis..and identification of this sickness by looking at Resnet-50, DenseNet121 and Alexnet. The dataset utilized was openly obtained from [19]. To discover the outcome, I did an examination test on three profound learning Situation A was Separating pneumonia patient and a non-pneumonia patient utilizing AlexNet Profound learning Model, Situation B was Recognizing pneumonia patient and a non-pneumonia patient utilizing ResNet 50 Profound learning Model, Situation C was Recognizing pneumonia patient and a non-pneumonia patient utilizing Thick Net 121 Profound learning Model. Trial result shows that from situation A the model displays strong execution across all measurements, with high exactness, responsiveness, explicitness, F1 score, and AUC. Such execution demonstrates the model's dependability in precisely recognizing pneumonia cases while limiting bogus up-sides and misleading negatives. This degree of execution holds guarantees for clinical applications. From Situation B shows that the model exhibits generally speaking great execution, there are regions for development. The high explicitness shows a low pace of bogus up-sides, which is critical for staying away from pointless mediations. Nonetheless, the awareness could be additionally improved to upgrade the discovery of pneumonia cases and decrease misleading negatives. Moreover, the F1 score recommends a sensible harmony between limiting bogus up-sides and misleading negatives, however further model enhancement might actually work on this equilibrium. Situation C shows that the model displays remarkable execution across all measurements, with high precision, awareness, particularity, F1 score, and AUC. Such execution demonstrates the model's dependability in precisely recognizing pneumonia cases while limiting misleading up-sides and bogus negatives. This degree of execution holds huge commitment for clinical applications. End

In this paper ANN could recognize and recognize a pneumonia patient and a non-pneumonia patient and profound learning design will be the best and effective in the conclusion and recognition of this sickness by looking at Resnet-50, DenseNet121 and Alexnet. It was determined from the trial that every one of the three models had the option to recognize and identify pneumonia precisely with no huge mistake.

IV. CONCLUSION

This showed how well ANN could detect and distinguish between a pneumonia patient and a non-pneumonia patient, and revealed which of these deep learning architectures could be the most effective and efficient in the diagnosis and detection of this disease through the use of Resnet-50, DenseNet121 and Alexnet models. It was found out from the experiments that all the three models were able to distinguish and detect pneumonia accurately with no significant error, also one of the models (DenseNet 121) showed a solid performance, DenseNet 121 consistently outperforms the other Architectures.

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