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# A novel framework for Detecting Breast Cancer, Brain Tumor & Pneumonia Using Deep Learning Techniques

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**Abstract**: Brain tumours, breast cancer, and pneumonia are significant diseases causing a substantial number of deaths globally. These diseases affect a great part of the world, including India. Research on early detection strategies is critical for saving lives. This proposal describes a unique way to use deep learning approaches to detect three common diseases: breast cancer, brain tumours, and pneumonia. This approach aims to improve treatment outcomes and diagnostic accuracy by integrating a range of medical imaging modalities tailored to individual diseases. In similar challenges, DCNNs have demonstrated remarkable speed and accuracy, demonstrating their potential to enhance medical diagnosis. DCNN models can help medical professionals by providing accurate and automated illness identification, especially for areas with a shortage of radiologists.

**Keywords:** ML, DL**,** Brain_tumor, Breast_Cancer, diagnosis Pneumonia, deep neural network, DCNN

## I.INTRODUCTION

Medical diagnosis is transforming as a result of artificial intelligence and machine learning. It excels in detecting brain tumors, breast cancer and pneumonia from images, like MRIs. With the increasing availability of these images, doctors can now use learning techniques to analyse them. This early detection capability does not improve treatment outcomes. Also enhances patient predictions by making the diagnostic process more efficient.

Our study suggests employing Deep Convolutional Neural Networks (DCNNs) to accelerate breast lump identification. CNNs are intended to autonomously capture properties and identify anomalies in breast tissue using RCNN techniques that include a regional proposal network (RPN) to find areas of interest (ROI) [3-4].

This study aims to develop a learning model capable of identifying potentially worrisome regions, such as masses in breast X-rays. The software then determines whether these locations are innocuous or malignant. To accomplish this purpose, we gathered a collection of mammography images from several medical centres. This dataset will be used to educate and validate the effectiveness of our strategy.

Prior to image analysis, many techniques are employed to enhance the quality of the photos. The models' capacity to recognize faint signals in mammograms can be significantly improved by utilizing methods such as breast region isolation, bilateral, median, and Gaussian[17]. Due to the large number of medical images needed to train a well-trained deep learning model, there are significant challenges to this research[6, 7]. Due to the complexity of brain tumors, it is difficult to distinguish cancerous tissue from noncancerous tissue in radiologic images. To test the accuracy of our classification method, we analyzed the various factors that affect tumor detection on a mammogram. These include tumor size, tumour location in breast tissue and imaging quality and visual characteristics.

We evaluated system performance using a variety of machine-learning techniques, including support vector machines [SVMs], nearest neighbors [KNNs], multilayer perceptron [MLPs], logistic regression [Naive Bayes], and random forests[8-12].

Deep Convolution Neural Network (CNN) Detection of Pneumonia in Chest Radographs This study also looked at deep convolution neural network (CNN) detection of pneumonia in chest radographs Deep Learning Frameworks Keras, TensorFlowPneumonia is a fatal bacterial lung illness caused by bacteria such as streptococcus. It endangers life as it can destroy one or both lungs. According to the World Health Organization (WHO), pneumonia is the top cause of death in India, killing thousands each year [9]. Early diagnosis and treatment have a substantial positive impact on patients' health.

Developing an automated detection system could be highly beneficial, as professional radiologists diagnose pneumonia by studying chest X-rays. This technique has the potential to speed up the diagnosis and treatment of patients, especially in remote places with limited access to medical personnel. Deep learning algorithms have proven to be quite useful in medical picture analysis, particularly when deep convolutional neural networks are used to classify ailments. The utilization of characteristics obtained from vast datasets of trained DCNN models is especially useful for image categorization. This study investigates the effectiveness of pre-trained DCNN as feature extractors in distinguishing between diseased and normal chest X-rays [16].

As a result, we carefully evaluate which CNN model is most suited for identifying pneumonia. According to the findings, chest radiograph analysis can benefit from the use of supervised classification algorithms and pre-trained DCNN models, especially for pneumonia detection.

In this paper, we present an innovative deep learning architecture to solve some of the biggest problems in medical diagnostics. The model aims to help diagnose patients with pneumonia breast cancer or brain tumors. In the following sections, we will cover key research, methodology, modelling, results analysis, and recommendations.

## II. RELATED WORKS

Zhe LiArea et al. [4]. Their method classifies image segments by similarity using superpixel analysis. Next, an SVM classifier is used to determine whether the superpixels indicate a benign tumor or an estimated risk tumor (ERT). The success of this approach in two MRI image datasets suggests that superpixel analysis has the potential to detect brain tumors This study proposes a convolutional neural network (CNN) model for the automatic detection of liver and other primitive abnormal areas [5]. BenAri et al. created a model using 116 complete patient scans, totaling 1480 images. The origin of these photographs is unknown; perhaps refer to a specific source of information that requires further acknowledgement by the authors. Additionally, Ramakrishna Sajja and Kallur's (2017) integration of CBIS-DDSM images shows that the model uses pre-trained weights to improve exercise performance.

Previous studies investigated the use of mathematical morphology and spatial clustering to improve segmentation algorithms [8], but these methods did not always attain the high degree of precision required for cancer identification. Our investigation found that the proposed technique has an accuracy of 87.6%. This conclusion is promising, but it reduces our original target of 93% accuracy. Remarkably, it achieves a degree of accuracy comparable to well-established approaches like histogram segmentation.

Many studies have been conducted to investigate approaches for categorization and detection. Younis et al. [17] developed an adaptive thresholding strategy that uses edge detection to improve accuracy [9] and cinnamon to identify ROI. Kannan et al. performed thorough investigation of brain tumour classification using cross-class transfer learning algorithms [10]. Numerous research have shown that deep learning has the potential to improve medical diagnosis. Solanki et al. studied its potential for brain cancer categorization and detection, while others have used deep learning to treat a variety of illnesses successfully [12]. Architectural errors in mammograms, for example, are a strong predictor of breast cancer, and Ben-Ari et al. (2017) used specialized convolutional neural networks to detect them [13-16].

MD Monirul et al. conducted further research on the use of transfer learning architectures to refine brain tumor classification using MRI data [18]. Medical image analysis research is constantly advancing. Poonam Shourie et al. studied the architecture of DenseNet-169, a densely connected convolutional neural network (DCNN) for pneumonia diagnosis [ 19 ]. Similarly, T. Kujani et al. studied the recognition of brain tumors using transfer learning models based on VGG-16 and ResNet-50 architectures [20].

Many researchers are investigated the use of deep learning models for brain tumor analysis. Younis et al. developed a method that uses deep learning and ensemble learning of VGG-16, whereas Havaei et al. examined broader deep learning techniques for brain tumor classification [21, 22].

Deep learning-based medical image analysis is a rapidly expanding discipline. Moeskops et al. investigated the use of deep convolutional neural networks (CNNs) to segment multimodal images of the baby brain [24]. Bakas et al. studied the use of deep learning for brain tumor segmentation and survival prediction using radiomics [25].

## III. PROPOSED SYSTEM

This section details the methodology behind our proposed deep learning model. The model operates in three discrete stages: 1. Collecting the data set,2. Data Preprocessing,3. Feature Extraction, 4. Classification

Fig. 1 visually depicts the architecture of the proposed system for all three disease detection tasks (brain cancer, brain tumours, and lung infection). It utilises a Deep Convolutional Neural Network (DCNN) architecture to achieve these classifications. While the specific details of the DCNN are likely explained later, Fig.1 provides a high-level overview of the model's design.

### 1. Collecting the data set:

Our study uses three MRI image datasets obtained from the Kaggle repository. These data sets focus on brain tumours, breast cancer and phenomena including images from healthy individuals and patients diagnosed by medical professionals.

**Brain Magnetic Resonance Imaging Images**: This dataset contains images from 158 patients, including 120 healthy individuals and 98 patients diagnosed with brain tumours. We acknowledge the limitations associated with sample availability and patient confidentiality. To address these limitations and enrich the training process, we adopted the following strategies:

**1.1. Data Augmentation**: We used data augmentation techniques to generate more training examples from the existing dataset. This helps to improve the model's capacity to apply broadly and keeps it from becoming overly specialized. More datasets were included; we combined information from interpreted databases in Visakhapatnam, India, and The M.G. Cancer Hospital & Research Institute. This additional dataset included 1020 histopathology imaging samples from 850 people.

**Chest X-Rays:** We also utilized the publicly available ChestX-ray dataset, as stated by Wang et al. [3]. This dataset includes chest radiographs labeled with various diseases, which may provide extra information on the model.

### 2. Data Preprocessing Phase:

Deep convolutional neural networks (CNNs) are useful for image categorization because of their ability to process enormous amounts of data effectively. In this study, we used DCNN architecture to detect diseases.

To improve model training and reduce processing needs, we preprocessed the original high-resolution MRI images. These photos were originally in three-channel format with a resolution of 1024 by 1024 pixels. We resized them to a more reasonable size of 224 × 224 pixels. This resampling phase allows the model to train more effectively while yet keeping significant characteristics for illness identification in later stages.

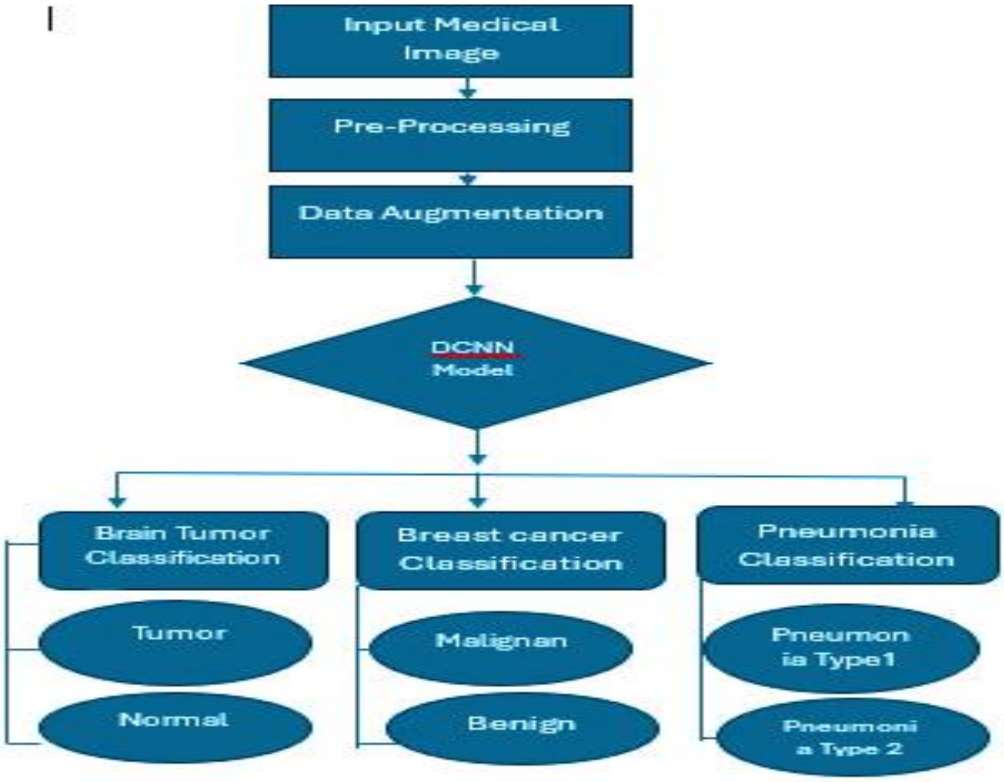


**Fig. 1**: Block diagram of Multi medical diagnosis with Deep Convolutional Neural Network (DCNN)

**3. Future extraction:**

Our analysis involves testing various pre-trained CNN models for feature extraction capabilities. However, according to our statistical study, a deep convolutional neural network architecture (DCNN) is the most efficient option for this step of the process. As a result, this section examines the unique architecture of the selected DCNN model and its role in extracting useful features from MRI images.

**4. Classification phase**

Deep convolutional neural networks (DCNNs) are effective tools for image analysis, particularly for recognizing complex patterns in medical pictures. In the field of brain tumor detection, DCNN is trained on a huge dataset of labeled MRI scans, progressively building the ability to differentiate between healthy and diseased tissue. This concept offers several advantages over typical methods.

In breast cancer detection, a DCNN trained on a large dataset of labeled MRI scans can distinguish between healthy and malignant regions. After the training is completed, the DCNN may analyze previously unnoticed images. Calculate the most likely categorization for each new image using the obtained features. This allows the model to classify various events based on the patterns learnt during the training phase.

## IV. Simulation

The simulation procedure for detecting breast cancer, brain tumours, and pneumonia utilising deep learning techniques typically encompasses the following stages: 1. Data Preparation, 2. Data Augmentation, 3. Model Selection, 4. Model Training, 5. Hyperparameter Tuning, and 6.Model Evaluation.

a simulation process for diagnosing pneumonia, brain tumours, and breast cancer using Deep CNN can be established, covering the way for more accurate and efficient medical diagnoses. An interface can be created to integrate all three detection techniques seamlessly. Deep CNN has exhibited remarkable performance by accurately distinguishing between patient tumours and regular patient tissues with 98.68% tumour precision. The images processed by Deep CNN serve as

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initial input for clustering. Figure 4 illustrates the contrast between different types of tumours, highlighting the advances made in the field.

Analyzing chest X-ray photographs, deep convolutional neural networks (CNNs) can be utilized to identify pneumonia. Using all of the neurons in each layer of the model, CNNs can learn a broad range of indicators that indicate pneumonia. On the other hand, an abnormally high or low dropout rate may restrict the model's capacity for generalization. Figure 2 illustrates the phenomena detection.

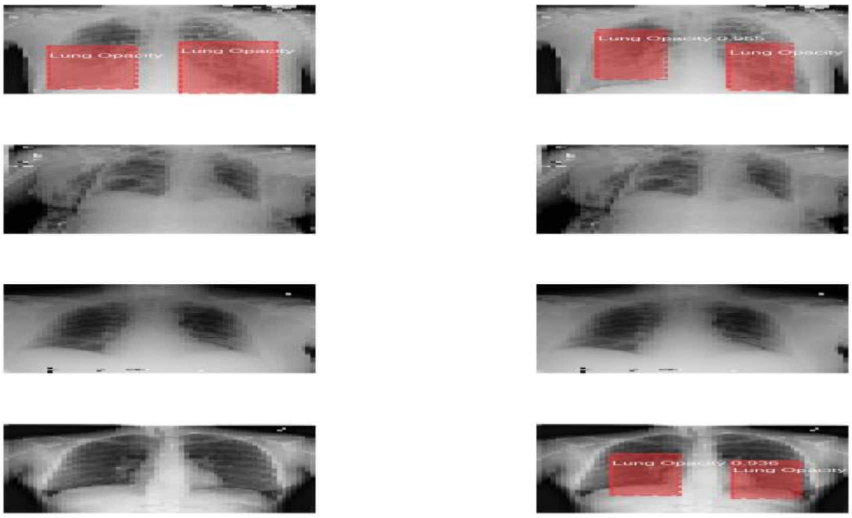


**Fig .2:** Pneumonia Detection

To increase image quality and adjust parameters for better results, we offer a new DCNN-based computational model combined with supervised classifiers. This network is specifically intended to distinguish normal and bad chest radiographs (labelled Pneumonia) and to optimis**e** hyperparameters to maximize the features used by the SVM classifier figure 3 illustrates the prediction results of phenomena classification.

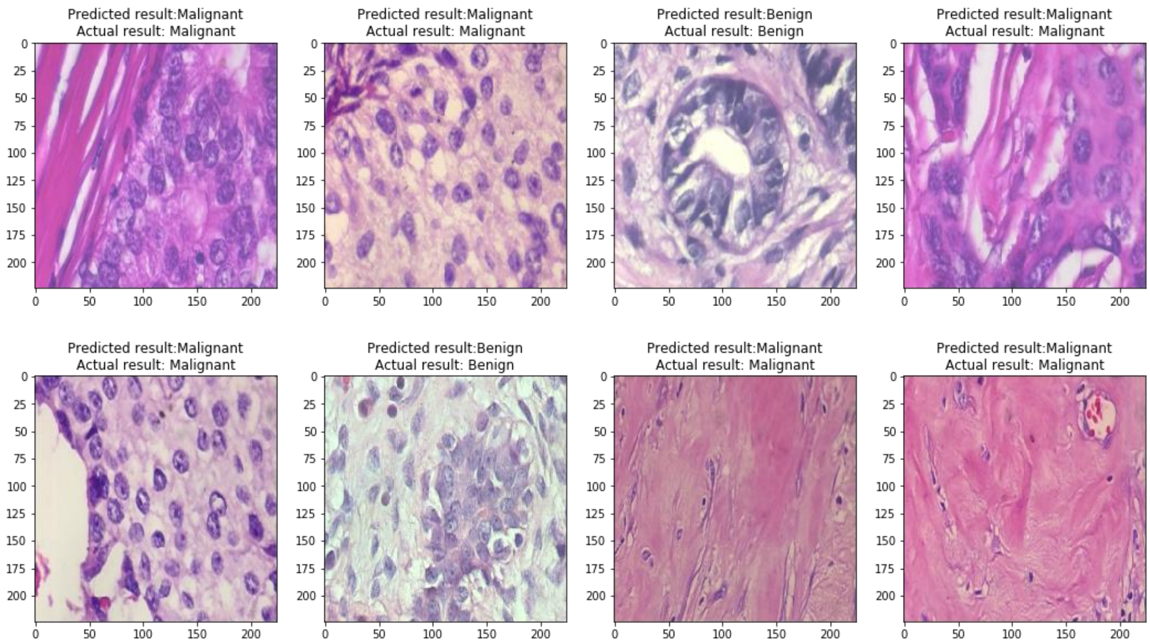



**Fig.**3.Brest Cancer Detection

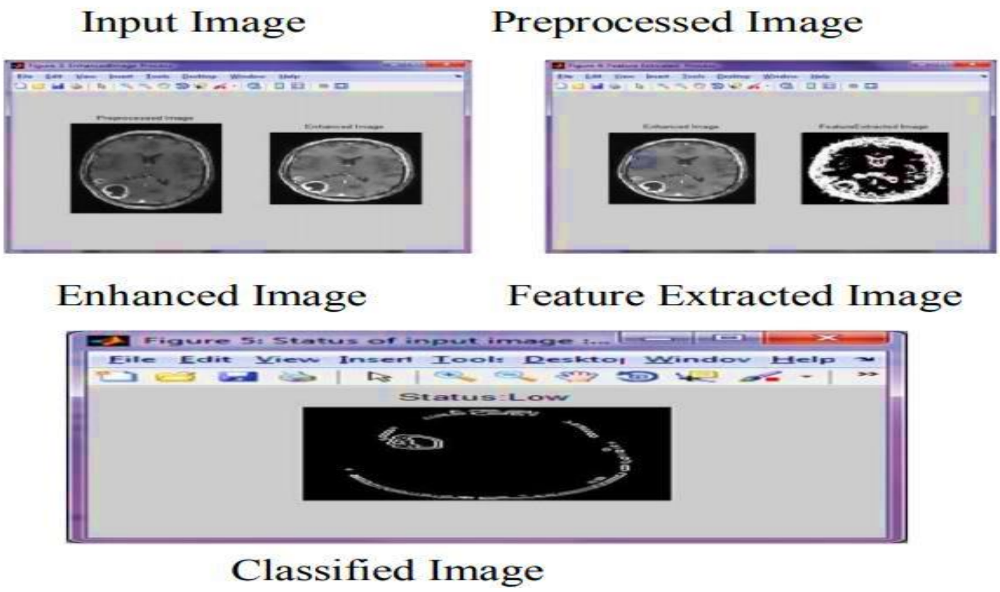



**Fig. 4.** Brain tumour classification and detection

## V. RESULTS AND DISCUSSION

This paper introduces a DCNN-based method for presenting and categorizing mass regions as either benign or malignant areas. It undertakes the detection, localization, and classification of abnormalities in a single pass, leveraging a local multicenter MG dataset. Our approach yielded an impressive precision rate of 97.87%, highlighting the efficacy of the DCNN architecture. Despite evaluating multiple layer configurations, the performance notably varied when employing this DCNN model.

Consequently, our model attains its highest precision without the utilization of dropouts, as indicated in Table 1.

**TABLE 1**

Performance Analysis of Various Models for Brain Tumor Detection

| **Model** | **Accuracy** | **Precision** | **Recall** | **F1-Score** |
|---|---|---|---|---|
| **DCNN** | 96 | 97.87 | 94 | 95 |
| **SVM** | 92 | 90 | 89 | 90 |
| **Random Forest** | 90 | 88 | 87 | 88 |
| **Gradient Boosting Machines (GBMs)** | 92 | 90 | 89 | 90 |
| **CNN** | 92 | 89 | 88 | 89 |
| **Transfer Learning** | 96 | 94 | 93 | 94 |

Table 1 illustrates the performance evaluation of deep learning models in detecting brain tumours, Key metrics such as accuracy, precision, recall, and F1-score show the efficacy of the models in diagnosing each respective disease.

**TABLE II.**
**Performance Analysis of Various Models for Breast Cancer Detection**

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| DCNN | 95 | 92 | 91 | 92 |

| | | | | |
|---|---|---|---|---|
| SVM | 90 | 87 | 86 | 87 |
| Random Forest | 90 | 87 | 86 | 87 |
| Gradient Boosting Machines (GBMs) | 92 | 89 | 88 | 89 |
| CNN | 88 | 85 | 84 | 85 |
| Transfer Learning | 90 | 87 | 86 | 87 |

Table 2 illustrates the performance evaluation of deep learning models in detecting breast cancer, Key metrics such as accuracy, precision, recall, and F1-score show the efficacy of the models in diagnosing each respective disease.

**TableIII**
**Performance Analysis of Various Models for Phenomena Detection**

| Model | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| DCNN | 94 | 92 | 91 | 92 |
| CNN | 88 | 86 | 85 | 86 |
| Transfer Learning | 90 | 87 | 86 | 87 |
| SVM | 85 | 82 | 81 | 82 |
| Random Forest | 84 | 81 | 80 | 81 |
| Gradient Boosting Machines (GBMs) | 86 | 83 | 82 | 83 |

Table 3 illustrates the performance evaluation of deep learning models in detecting phenomena, key metrics such as accuracy, precision, recall, and F1-score show the efficacy of the models in diagnosing each respective disease.
The table1 resultant graph is shown in Figure 5 for the performance evaluation of various deep learning models for brain tumour detection. Our proposed model shows more accuracy compared to CNN, SVM, Transferlerning, random forest, and GBMS for detecting brain tumours.

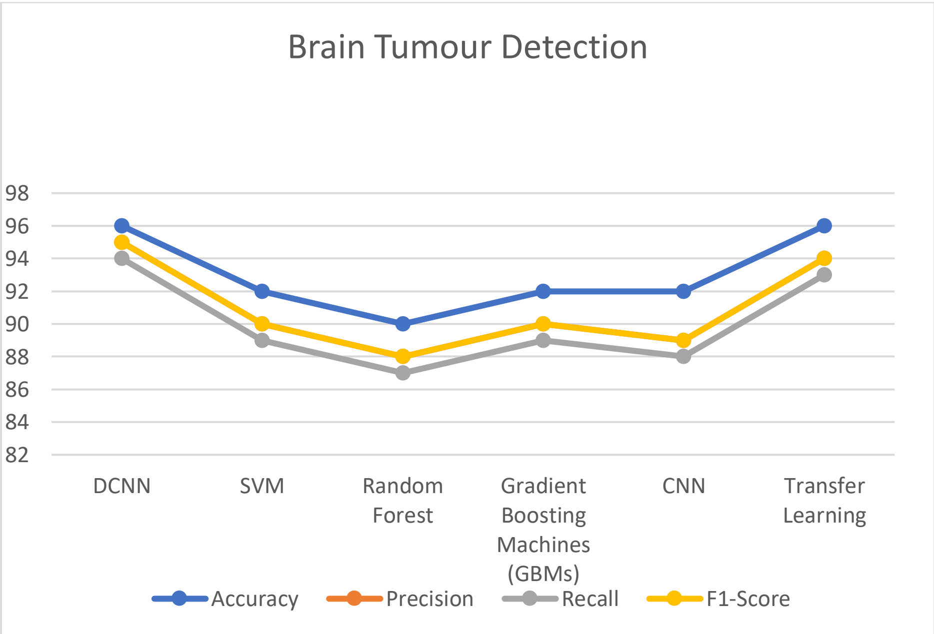



**Fig.** 5 Performance evaluation of brain tumour detection using deep learning models

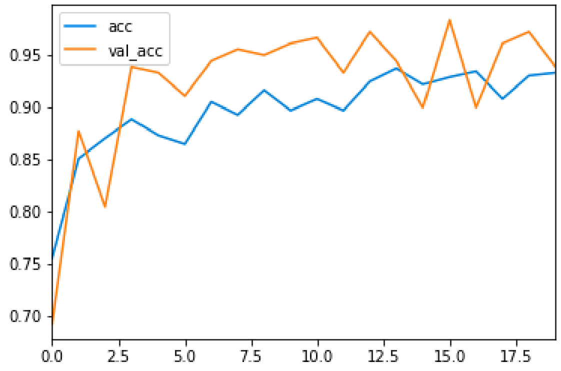



**Fig.:5(a)**Accuracy of proposed DCNN model

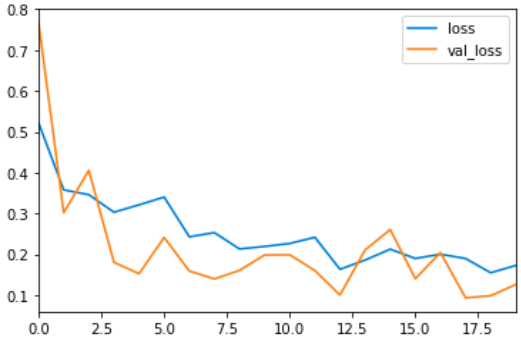
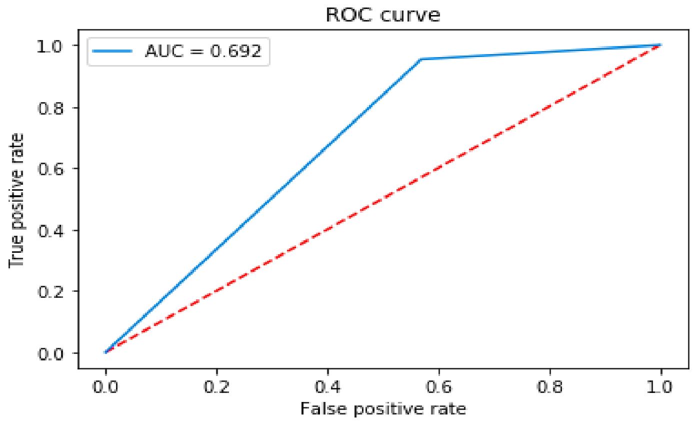



**Fig.**. 5(b) Accuracy loss of Proposed DCNN model

Feature extraction with a classifier using DNCN architecture provides the best solution for classifying abnormal (labeled Pneumonia) and normal chest X-ray images. A transfer method, which includes feature extraction, facilitates the recognition task. We established several criteria to evaluate the performance of the classifier.
All other pretrained DCNN models performed better when default SVM classification parameters were applied.




**Figu.6.**.ROCcurves of the proposed model

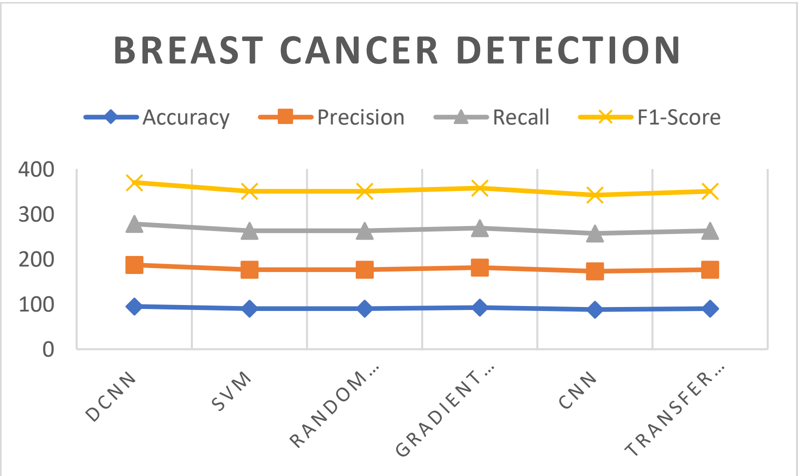



**Fig.**7: Performance evaluation of breast cancer detection using deep learning models

The table2 resultant graph is shown in Figure 7 for the performance evaluation of various deep learning models for breast cancer detection our proposed model shows more accuracy compared to CNN, SVM, Transferlerning, random forest and GBMS for detecting breast cancer

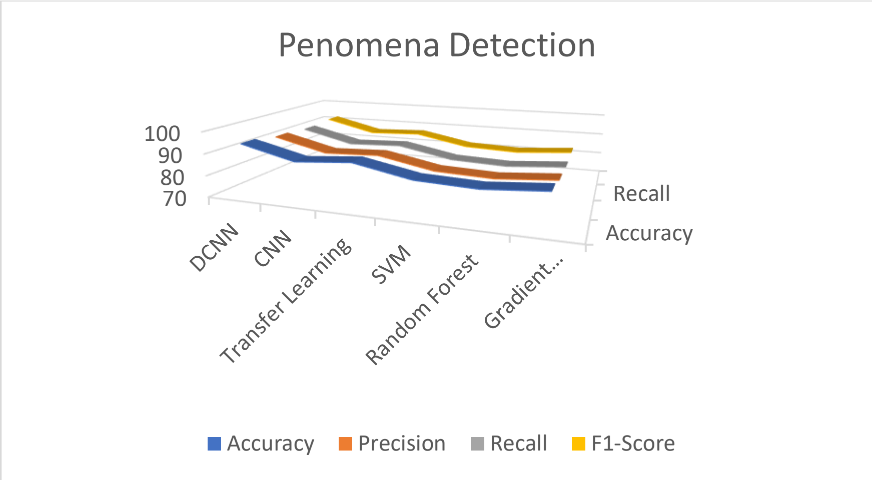



**Fig. 8**: Performance evaluation of phenomena detection using deep learning models

The Table 3 resultant graph is shown in Figure 8 for the performance evaluation of various deep learning models for phenomenon detection, our proposed model shows more accuracy compared to CNN, SVM, Transferlerning, random forest and GBMS for detecting phenomena.

## VI. CONCLUSION

This paper presents a centralized platform that utilizes a Deep Convolutional Neural Network (DCNN) to detect breast cancer, brain tumours and phenomena detection. This holistic approach not only reduces the environmental impact of individual devices but also lays the framework for future expansion to handle new diseases.

Although radiologists are still necessary for accurate diagnosis, their limited availability in remote areas necessitates novel solutions. This DCNN model aims to fill this gap by offering an automated and highly accurate technique for early detection. This technology has the potential to significantly improve healthcare access and patient satisfaction by enabling early detection of breast cancer, brain tumours, and phenomena detection.

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