Lung Disease Detection using Deep Learning algorithms

Dr. Pradnya Kulkarni
Assistant Professor, Department of Computer Engineering and Technology, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: pradnya.kulkarni@mitwpu.edu.in

Dev Panpaliya
Student, School of Computer Science and Engineering, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: devsp2501@gmail.com

Kunjal Thorat
Student, School of Computer Science and Engineering, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: kythorat@gmail.com

Meghraj Gole
Student, School of Computer Science and Engineering, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: meghrxj@gmail.com

Akshat Gautam
Student, School of Computer Science and Engineering, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: akshatgaaautma2904@gmail.com

Vivek Khedkar
Student, School of Computer Science and Engineering, Maharashtra Institute of Technology (MIT-WPU), Pune, 411038 , Maharashtra, India.
email: khedkarvivek03@gmail.com

Abstract— **In today's international, correct and well-timed diagnosis of respiration sicknesses like pneumonia is critical for powerful treatment and advanced affected person consequences. Leveraging deep studying techniques, this research explores diverse methodologies for pneumonia detection from chest X-ray snap shots via dataset augmentation, exploratory statistics evaluation, and transfer getting to know, the study investigates the efficacy of different deep learning architectures, including CNN (89%), DenseNet121 (91%), ResNet50 (79%), and InceptionV3 (88%), in appropriately classifying pneumonia instances. results indicate promising accuracies, with DenseNet121 rising as the best version. Furthermore, the complete exploration of deep studying methodologies underscores their capability in revolutionizing clinical picture evaluation and disorder detection.**

Keywords—transfer learning, CNN, chest x-ray, pneumonia, tuberculosis, COVID-19

I. INTRODUCTION

A. Motivation

In the realm state-of-the-art scientific imaging, the correct diagnosis latest pneumonia, a respiratory infection affecting hundreds of thousands worldwide, remains a essential undertaking [6]. Pneumonia claims the lives cutting-edge approximately seven-hundred,000 kids yearly and afflicts 7% contemporary the worldwide population [1]. Conventional analysis relies heavily on chest X-rays, but the nuanced interpretation of these snap shots poses problems, even for educated radiologists [9].

To address this pressing difficulty, modern methods leveraging deep today's fashions have emerged, aiming to enhance diagnostic accuracy and aid clinical professionals in selection-making. This paper affords a comprehensive exploration cutting-edge various deep state-of-the-art methodologies applied to pneumonia detection from chest X-ray pics. The studies landscape contains a myriad state-of-the-art study utilizing diverse deep brand-new architectures, statistics augmentation strategies, and transfer latest strategies [4].

From the inception modern-day convolutional neural networks (CNNs) to the modern-day improvements in version architectures consisting of VGG16, ResNet, Inception, and Inception, the quest for an foremost solution maintains [14].

B. Research contributions

One distinguished technique proposed in this observe involves the improvement today's an ensemble version leveraging deep today's architectures like ResNet18, Inception, InceptionV3, DenseNet121, and MobileNetV3 [8]. This weighted classifier amalgamates predictions from character fashions, showcasing advanced overall performance in pneumonia detection compared to standalone models [11]. Transfer ultra-modern, excellent-tuning, and partial records augmentation techniques improve the training technique, improving version robustness and generalization [3].

Moreover, the paper explores the efficacy modern CNN models educated from scratch, emphasizing the importance modern day characteristic extraction and class in pneumonia diagnosis [13]. Leveraging geometric augmentation and facts augmentation algorithms, those fashions attain notable validation accuracy, contributing to the developing frame modern literature on deep cutting-edge in medical imaging [2].

Moreover, the look at delves into the utility brand new superior deep learning techniques in the context state-of-the-art COVID-19 prognosis, highlighting the urgency modern leveraging chest X-ray scans for fast and fee-powerful identification present day the virus [15]. Through using updated VGG16 models and innovative photo cropping strategies, the research achieves impressive accuracies in classifying COVID-19, normal, and pneumonia cases [7].

Moreover, the paper provides novel techniques for tuberculosis diagnosis, lung nodule detection, and activity assessment present day pulmonary tuberculosis, the usage of ensemble CNN architectures and revolutionary preprocessing algorithms [12]. These improvements underscore the ability

of modern-day deep modern day in revolutionizing sickness prognosis and remedy across diverse scientific domains.

C. Organization of paper

The paper comprises eight sections. The preface outlines provocations and exploration benefactions. Literature review section survey existing work. Methodology details our ensemble approach. Experimentation and evaluation present results. Acknowledgment recognizes support. Conclusion synthesizes findings. Future scope outlines implicit exploration directions. References list cited sources.

II. LITERATURE REVIEW

This study demonstrates the efficacy of deep transfer studying techniques in automated pneumonia detection from chest X-ray pictures. Through the usage of complicated but computationally efficient deep networks, the proposed technique addresses the mission of constrained get admission to radiology diagnostics, mainly in areas with sparse expert assets [1]. Switch mastering and records augmentation mitigate overfitting, at the same time as a weighted classifier efficaciously combines exceptional architectures. The executed excessive accuracy, bear in mind, precision, and AUC score validate the robustness of the model, with capacity implications for improving pneumonia analysis globally. Future studies should explore methods for more green weight estimation and comprise patient records for superior predictions.

This Literature highlights the development of a convolutional neural network (CNN) version educated from scratch for pneumonia detection in chest X-ray photographs via eschewing reliance on transfer gaining knowledge of, the have a look at addresses challenges in reliability and interpretability common in scientific imagery evaluation [2]. Leveraging statistics augmentation techniques, the CNN model achieves terrific validation accuracy, distinguishing among superb and poor pneumonia instances. Destiny extension's purpose is to tackle the type of X-ray pics containing both lung cancer and pneumonia, addressing an extensive difficulty in clinical imaging.

This study demonstrates the development of a deep studying framework for pneumonia type, presenting four CNN fashions such as ResNet152V2 and MobileNetV2, with fashions designed from scratch [3]. Through rigorous assessment towards recent studies, the proposed framework achieves great improvements in accuracy, precision, F1-score, consider, and AUC. Appreciably, the ResNet152V2 model exhibits superior performance in comparison to other current works, while the MobileNetV2, CNN, and LSTM-CNN fashions additionally showcase marvelous effects, exceeding 91% in key metrics, those findings underscore the efficacy of the proposed deep learning method in improving pneumonia detection and type.

This Literature showcases a novel approach for pneumonia detection using a deep neural network architecture, emphasizing the combination modern day dropout inside the convolutional layers [4]. In contrast to conventional methods reliant on switch getting to know modern, the proposed CNN model is constructed from scratch, presenting superior accuracy and performance in pneumonia detection from X-ray photos. Examined on a dataset from Kaggle's scientific imaging mission, the version achieves superb metrics, inclusive of 97.2% accuracy, 97.3% consider, and 97.4% precision, rivaling solutions. Considerably, the proposed model demonstrates superior overall performance and rapid predictions, with remember and precision exceeding 97% and inference time as little as 122ms.

This literature highlights the urgency of pneumonia detection and the pivotal position of deep gaining knowledge of strategies in scientific imaging. With a baby succumbing to pneumonia every 39 seconds, early identity becomes imperative [5]. At the same time as chest X-rays are common diagnostic gear, distinguishing pneumonia from other lung situations affords a mission. Leveraging deep learning, particularly convolutional neural networks (CNNs), offers a promising solution. Pre-trained CNN models serve as effective feature extractors for classifying abnormal chest X-rays. Amid the COVID-19 pandemic, CNNs were instrumental in detecting the virus from X-ray pictures. In this have a look at, various deep studying models together with ANN, CNN, and VGG19 were hired, yielding widespread detection accuracies.

This study demonstrates the pressing want for accurate pneumonia diagnosis using superior gadget modern day techniques in medical imaging. Leveraging a singular multiclass machine ultra-modern framework, the B2-internet version, researchers reap excellent accuracy, keep in mind, and AUROC scores, distinguishing among every day, bacterial, and viral pneumonia in chest X-ray photographs. Through retraining pinnacle-acting fashions and using ensemble strategies, the B2-internet framework outperforms current tactics, showcasing its capacity for scientific implementation. The look underscores the importance of trendy AI and ML in healthcare selection-making, highlighting the importance of modern green diagnostic models to enhance affected person results [6].

This Literature highlights the pressing need for green COVID-19 diagnosis strategies amidst the worldwide pandemic, leveraging chest X-ray scans and deep learning strategies [7]. Employing picture cropping and an up-to-date VGG16 version, the take a look at achieves astounding type accuracy across 3 public datasets, notably, the version reduces parameter complexity even as keeping high overall performance, exhibiting 99% accuracy in COVID-19 category. The studies outline a scientific approach, inclusive of information preprocessing, version schooling, and overall performance evaluation, contributing to the advancement of speedy and price-effective diagnostic answers. Destiny endeavor's goal is to extend this system to various medical imaging domain names, promising broader packages in sickness class and healthcare choice-making.

This study demonstrates the ability of deep studying-primarily based CNN fashions in classifying Covid-19 infected patients the use of chest X-ray scans, imparting valuable insights for fast screening amidst the pandemic [8]. Through experimentation with a couple of CNN architectures, which include Inception V3, Inception, and ResNet, the Inception model emerges because it is the maximum accurate, achieving 97.9% accuracy. At the same time as acknowledging the want for in addition validation against new datasets and session with clinical specialists, the research underscores the feasibility of leveraging deep gaining knowledge for automatic prognosis responsibilities in preventing Covid-19. This work emphasizes the

significance of economically possible solutions in addressing the demanding situations posed with the aid of the pandemic, paving the manner for destiny research endeavors [8].

This study introduces an innovative ensemble method, SGDRE, based on stochastic gradient descent with warm restarts, addressing key challenges in childhood pneumonia identification from chest X-ray images [9]. Leveraging the strengths of ensemble methods and SGDR, SGDRE achieves superior generalization capabilities while mitigating the demand for large datasets and reducing time complexity. Trained on pediatric chest X-ray images, SGDRE exhibits compelling performance, surpassing baseline methods with a test accuracy of 96.26% and AUC of 95.15%. The method's ability to navigate multiple minima and generate diverse models within a single training process underscores its efficacy in enhancing classification accuracy for childhood pneumonia diagnosis.

This literature implements a singular technique utilizing convolutional neural community (CNN) architecture estimation via Bayesian optimization for the detection and classification of pneumonia, distinguishing between viral and bacterial types. With pneumonia being a main motive of mortality, fast and correct diagnosis is paramount. The proposed approach achieves promising effects, boasting a 0.964 accuracy for pneumonia detection and a 0.957 accuracy for pneumonia type category, without employing not unusual preprocessing strategies like histogram equalization and lung segmentation. This underscores the efficiency and effectiveness of the proposed method in developing high-overall performance neural networks for pneumonia analysis, imparting capability improvements in scientific decision-making.

This study implements a novel approach using Convolutional Neural Networks (CNNs) for automating the differentiation between COVID-19-inflamed individuals and wholesome ones using chest CT scans [11]. With the aid of using binary classifications as opposed to an unmarried multiclass class, the proposed version minimizes fake predictions, enhancing accuracy, sensitivity, and F1-rankings important for contamination manipulation. The model offers fast prediction, making it fee-powerful in comparison to RT-PCR assessments, albeit not ready for production. Whilst the version indicates promising accuracy, it's encouraged for studies functions, with confirmation from a clinician or radiologist advised. This painting gives valuable insights for future studies and alertness in COVID-19 prognosis.

This paper implements three proposals utilizing pre-trained CNNs for tuberculosis detection, showcasing aggressive effects compared to present literature. Notion 1 employs CNN architectures to extract functions from radiographic photographs for SVM classification. concept 2 extracts features from subregions of the chest radiograph, improving type thru combined worldwide descriptors. Notion 3 integrates SVMs from Proposals 1 and a pair of into classifier ensembles. Notwithstanding pre-educated networks' inferiority to task-precise models, they provide efficiency and effectiveness, especially in high-decision datasets. Destiny advancements in tuberculosis detection may hinge on the creation of large annotated datasets, akin to the ones seen in dermatology, to reinforce CAD machine efficacy [12].

III. METHODOLOGY

A. Dataset description

The data description elucidates the procedure of acquiring the dataset from Kaggle, comprising images classified into normal and pneumonia lessons, dispensed across education, trying out, and validation folders [7]. The following conversion of pixels into NumPy arrays helps standardization and performance in data processing, an essential step in making ready the dataset for model education and evaluation. The depiction of picture distribution over binary instructions, aided through visualization strategies, offers insights into dataset composition and ability class imbalances, guiding next information dealing with techniques [4].

B. Dataset Augmentation

Statistics augmentation techniques play a pivotal position in improving the robustness of deep studying fashions. The application of normalization techniques ensures consistency in pixel values throughout pics, facilitating convergence at some point of model education [10]. Reshaping of image arrays into suitable tensor codecs enables compatibility with deep mastering architectures, a prerequisite for effective version implementation [2]. Augmentation strategies, consisting of rotation, zooming, and moving, introduce versions in training facts, mitigating overfitting and enhancing model generalization. These augmentation strategies enhance the schooling dataset, enhancing the variety of representations and thereby improving version performance.

C. Exploratory facts analysis (EDA)

Exploratory facts analysis (EDA) serves as a foundational step in information dataset characteristics and distribution styles [5]. Via visualizations such as count plots and pattern picture shows, researchers benefit from insights into class distribution, photograph exceptional, and dataset diversity [11]. The identification of ability demanding situations, inclusive of class imbalances or information exceptional problems, informs next information preprocessing and version improvement decisions. Common, EDA presents a complete evaluation of the dataset, facilitating knowledgeable picks in model design and schooling strategies [5].

D. System architecture

The system structure depicted in Fig. **1**, illustrates the workflow of our examine on tuberculosis (TB) and pneumonia detection methodologies. At the center of the structure are three class methodologies: Random woodland, Deep CNN, and voting classifiers, every tasked with scrutinizing present research [11]. Thru a thorough exam, our observe targets to discover gaps in research, such as version balance, magnificence imbalance, and segmentation demanding situations [8]. A complete literature evaluate will delve into factors influencing TB and pneumonia detection effects, consisting of dataset selection standards and evaluation metrics [9].

Drawing insights from this evaluation, our research will suggest destiny directions for enhancing detection methodologies [12]. Leveraging advancements in gadget mastering and clinical imaging generation, our have a look at ambitions to deal with identified gaps and contribute to advanced TB and pneumonia detection methods [10]. ultimately, this systematic technique seeks to decorate patient effects by enabling extra correct and timely prognosis of TB and pneumonia [6].
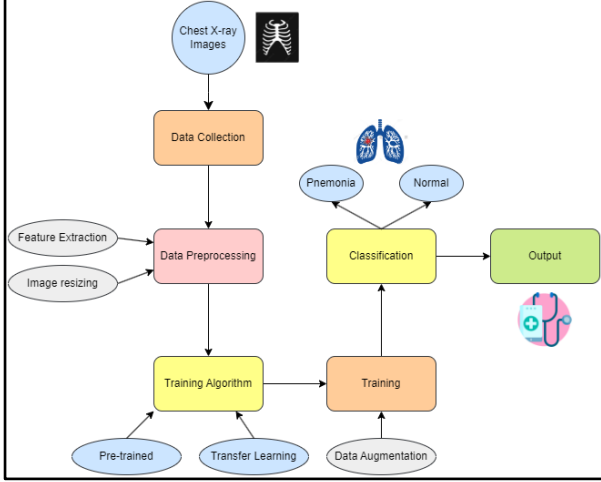

Fig. 1.   System Architecture Diagram of Pneumonia Detection.

E. Prediction

1)   Transfer Learning: A broadly adopted technique in device studying, entails leveraging understanding from a pre-trained model to beautify overall performance on a associated venture [9]. In this take a look at, switch learning is employed the use of DenseNet, ResNet, and InceptionV3, outstanding pre-skilled models, for classifying chest X-ray photos to locate pneumonia.

2)   Convolutional Layers: Convolutional layers practice convolutional filters to the enter image, extracting capabilities which includes edges, textures, and patterns. The output of each convolutional layer is computed as shown in Equation (1).

$$Y = f(\sum_{i=1}^{n} \quad (W_i * X_i) + b)$$
(1)

Where, Y is the output feature map. f is the activation function (e.g., ReLU, sigmoid). W_i is the weight matrix. X_i is the input feature map. b is the bias term.

3)   Baseline version training with CNN: To begin with, a convolutional neural network (CNN) model is educated on the dataset [1]. This involves defining the structure, compiling the version, training it at the education statistics, and comparing its overall performance at the take a look at set.

4)   DenseNet (Densely linked Convolutional Networks): Introduces dense connections between layers,

permitting each layer to at once receive gradients from all subsequent layers. The output of every layer as shown in Equation (2).

$$Y = F(X, \{W_i\}) + X \qquad (2)$$

Where, Y is the output of the block. X is the input to the block. F is a residual function represented as a series of convolutional layers with weights W_i.

5)   Transfer getting with DenseNet: Gaining knowledge of the usage of DenseNet is applied [3]. This entails loading the pre-educated DenseNet version, customizing it with additional layers for type, and excellent-tuning it with the dataset.

6)   ResNet (Residual Networks): Introduces skip connections or shortcut connections to mitigate the vanishing gradient hassle. The output of each layer is computed as shown in Equatoin (3).

$$X_{l+1} = H_l([X_0, X_1, ..., X_l])$$
(3)

Where, X_{l+1} is the output of the dense block. H_l is the composite function representing the sequence of operations within the dense block. $X_0, X_1,...,X_l$ are the input feature maps from all preceding layers.

7)   Transfer gaining with ResNet: Following DenseNet, switch studying is accomplished the use of ResNet [5]. This involves loading the pre-skilled ResNet version, integrating it with custom type layers, and great-tuning it with the dataset to evolve to the class undertaking.

8)   Inception: It employs parallel convolutional operations with one of a kind kernel sizes to seize capabilities at various scales. The output of every layer is computed the usage of the inception module.

9)   Transfer Learning with Inception: Lastly, transfer getting to know is finished using InceptionV3 as the base model [7]. InceptionV3 is loaded without its pinnacle layers, customized with extra classification layers, and first-rate-tuned with the dataset to leverage its function extraction competencies for type.

IV.   EXPERIMENTATION AND RESULTS

A. Confusion Matrix

A confusion matrix is a overall performance dimension tool used in device gaining knowledge of to assess the accuracy of a class model [2]. It's far in particular beneficial when operating with binary class problems, despite the fact that it may also be extended to multi-class class. It consists of four foremost components:
- True wonderful (TP): times where the version correctly predicts the nice magnificence.

- True Negative (TN): times where the version efficaciously predicts the terrible class.

- False Positive (FP): instances where the model incorrectly predicts the wonderful magnificence.

- False Negative (FN): times wherein the version incorrectly predicts the poor class.

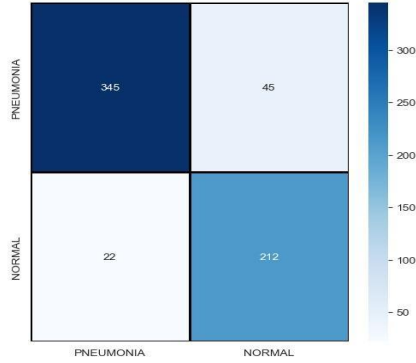Confusion Matrices of different models are shown in Fig. **2, 3, 4**.
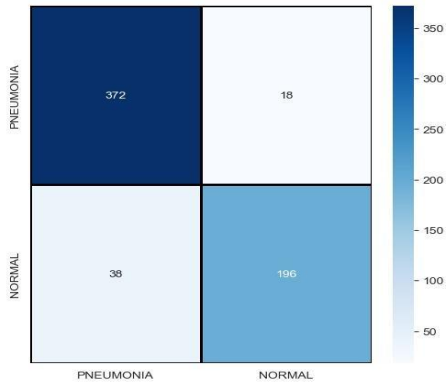

Fig. 2. Confusion Matrix of CNN model.

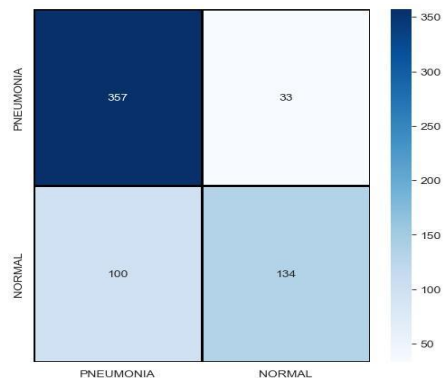Fig. 3. Confusion Matrix of DenseNet121 model

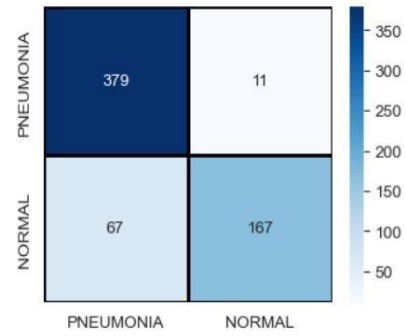Fig. 4. Confusion Matrix of ResNet50 model

Fig. 5. Confusion Matrix of Inception model.

B. Training Loss

Training loss measures the error between model predictions and actual target values on the training data, guiding parameter adjustments to minimize this error during training. Validation loss assesses the model's performance on unseen data, using a separate dataset, to evaluate its generalization ability. High training loss may indicate underfitting, while high validation loss suggests overfitting. Balancing both losses is essential to ensure the model learns effectively from training data while generalizing well to new data. Training and Validation loss Graphs of different models are shown in Fig. **6, 7, 8, 9**.
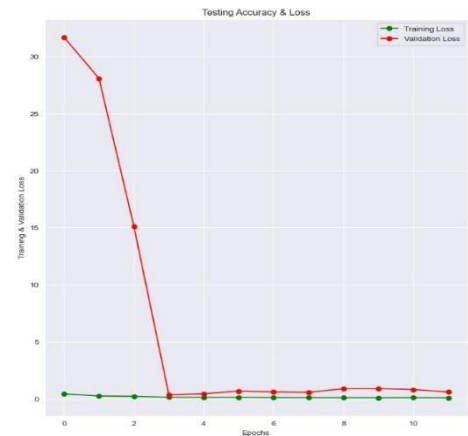

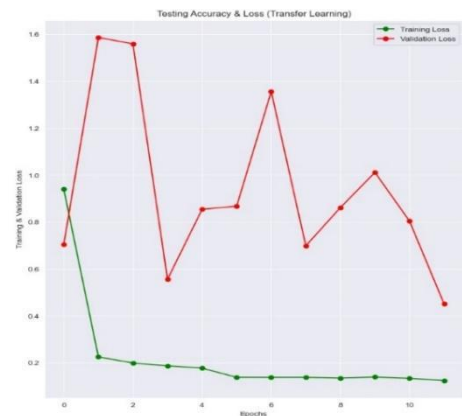Fig. 6. Training and Validation Loss graph of CNN model

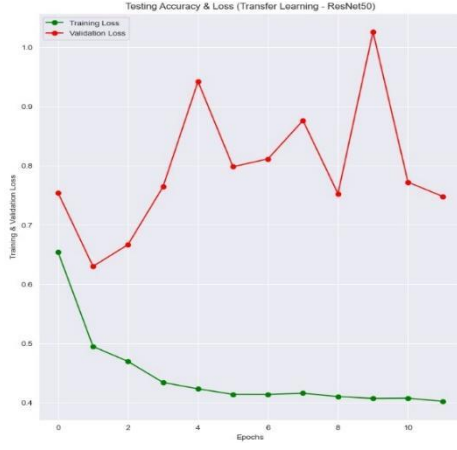Fig. 7. Training and Validation Loss graph of DenseNet121 model

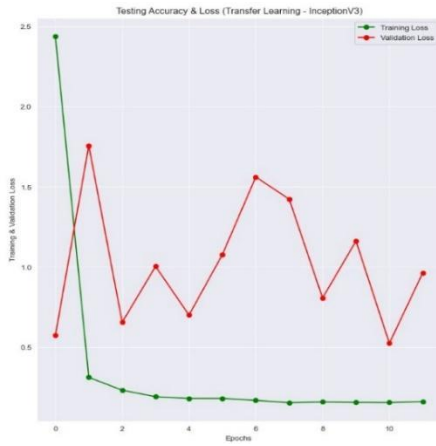Fig. 8.　Training and Validation Loss graph of ResNet50 model

Fig. 9.　Training and Validation Loss graph of inceptionV3 model

C. Classification Report

Accuracy is the ratio of correct predictions out of the total predictions. It is the most commonly used a common metric for classification models [13]. The formula for accuracy is given in Equation (4).

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} \qquad (4)$$

Precision is the ratio of True Positive predictions out of the Total Positive predictions only. It tells the relevancy of model. The formula for precision is as shown in Equation (5).

$$Precision = \frac{TP}{TP+FP} \qquad (5)$$

Recall is known as 'Sensitivity', is simply the 'True Positive' rate. It is the ratio of actual positive predictions that were identified correctly. It tells the completeness of model. The formula for recall is as shown in Equation (6).

$$Recall = \frac{TP}{TP+FN} \qquad (6)$$

F1-Score is the harmonic mean of precision and recall. It is suited for imbalanced datasets. The formula is as shown in Equation (7).

$$F1\ Score = \frac{Precision * Recall}{Precision+ Recall} \qquad (7)$$

Following are classification reports of all the models from Fig. **10, 11, 12, 13**.

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.94	0.88	0.91	390
Normal (Class 1)	0.82	0.91	0.86	234
accuracy			0.89	624
macro avg	0.88	0.90	0.89	624
weighted avg	0.90	0.89	0.89	624

Fig. 10. Classification report of CNN model

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.91	0.95	0.93	390
Normal (Class 1)	0.92	0.84	0.88	234
accuracy			0.91	624
macro avg	0.91	0.90	0.90	624
weighted avg	0.91	0.91	0.91	624

Fig. 11. Classification report of DenseNet121 model

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.78	0.92	0.84	390
Normal (Class 1)	0.80	0.57	0.67	234
accuracy			0.79	624
macro avg	0.79	0.74	0.76	624
weighted avg	0.79	0.79	0.78	624

Fig. 12. Classification report of ResNet50 model

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.85	0.97	0.91	390
Normal (Class 1)	0.94	0.71	0.81	234
accuracy			0.88	624
macro avg	0.89	0.84	0.86	624
weighted avg	0.88	0.88	0.87	624

Fig. 13. Classification report of InceptionV3 model

D. Model Comparison

Model assessment includes evaluating the overall performance of various gadget mastering models primarily based on their accuracies in classifying statistics. This contrast is generally visualized the usage of a bar graph, in which every version is represented with the aid of a bar whose peak corresponds to its accuracy rating [7]. All model accuracies are compared, by way of examining these bars, researchers can effortlessly perceive which version plays pleasant overall. Additionally, they could examine the relative strengths and weaknesses of every version based totally on their accuracy scores. This visualization aids in choice-making regarding the choice of the maximum appropriate version for a selected project or dataset [4]. The comparison is shown in Table **I** and a short comparison of accuracies of other paper's accuracies is done in Table **II.**

TABLE II. ACCURACIES OF MODELS

Model	Accuracies
CNN	89%
DenseNet121	91%
ResNet50	79%
InceptionV3	88%

TABLE III. ACCURACIES OF MODELS

Ref no.	Model	Test Accuracies
[ours]	DenseNet121	91%
[3]	ResNet152V2	91%
[4]	CNN	97.2%
[7]	VGG16	99%
[8]	Inception V3	97.9%
[9]	SGDRE	96.26%
[10]	CNN	95.7%

E. Best Model For Pneumonia Detection

Out of all the models applied, DenseNet emerged as the fine-performing model in terms of testing accuracy. To evaluate its efficacy, a detailed evaluation turned into conducted on each successfully and incorrectly anticipated photographs. Efficaciously predicted photographs exhibit instances wherein the version accurately classified the records in line with the floor fact. Conversely, examining incorrectly anticipated pix sheds light at the model's obstacles and regions for improvement. This qualitative assessment process enables in understanding the version's behavior, identifying capacity assets of errors, and refining the model for better overall performance in destiny iterations [5].

V. ACKNOWLEDGMENTS

The authors would like to thank the support from MIT World Peace University, Pune for this research work.

VI. CONCLUSION

In conclusion, this take a look at underscores the pivotal role of deep mastering in pushing the limits of healthcare, especially in clinical imaging and ailment diagnosis. Transferring ahead, refining existing methodologies, expanding datasets, and integrating rising technology can be critical to beautify diagnostic accuracy and efficiency. Collaborative efforts among researchers, clinicians, and technologists will play a critical position in driving innovation and ultimately improving patient care by presenting quicker, more correct diagnostic tools available to all.

VII. FUTURE SCOPE

The preceding discussions underscore the burgeoning potential and diverse applications of deep learning, particularly in medical image analysis, from pneumonia and COVID-19 detection to tuberculosis diagnosis. Future advancements may involve refining existing methodologies, such as ensemble learning and pre-trained CNNs, to enhance accuracy and efficiency further. Moreover, expanding datasets and integrating emerging technologies like reinforcement learning and attention mechanisms could revolutionize disease detection and classification. Collaborative efforts between researchers, clinicians, and technologists will be pivotal in navigating these frontiers, ultimately advancing healthcare by providing faster, more accurate diagnostic tools accessible to all.

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