iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** VI **Month of publication:** June 2021

DOI: https://doi.org/10.22214/ijraset.2021.35294

www.ijraset.com

Call: 08813907089 | E-mail ID: ijraset@gmail.com

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue VI Jun 2021- Available at www.ijraset.com

Pneumonia Detection using Chest X-Ray Images

Shruti Meshram[1], Suhani Thaware[2], Amarendra Kumar Jha[3], Amit Pali[4], Mayur Khobragade[5], Dr. Virendra K. Taksande[6]
[1,2,3,4,5]*B.E. Students,* [6]*Professor, Department of Electronics & Telecommunication Engineering*
Priyadarshani College of Engineering, Nagpur, Maharashtra, India.

Abstract: ***Pneumonia is among the top diseases which cause most of the deaths all over the world. Virus, bacteria and fungi can all cause pneumonia. However, it is difficult to judge the pneumonia just by looking at chest X-rays. The aim of this study is to simplify the pneumonia detection process for experts as well as for novices. We suggest a novel deep learning framework for the detection of pneumonia using the concept of transfer learning. In this approach, features from images are extracted using different neural network models pre-trained on Image Net, which then are fed into a classifier for prediction. We prepared five different models and analyzed their performance. Thereafter, we proposed an ensemble model that combines outputs from all pre-trained models, which outperformed individual models, reaching the state-of-the-art performance in pneumonia recognition. Our ensemble model reached an accuracy of 96.4% with a recall of 99.62% on unseen data from the Guangzhou Women and Children's Medical Center dataset.***

Keywords: Deep learning; transfer learning; medical image processing; computer-aided diagnosis

I. INTRODUCTION

Today's deep learning models can reach human-level accuracy in analyzing and segmenting an image The medical industry is one of the most prominent industries, where deep learning can play a significant role, especially when it comes to imaging. All those advancements in deep learning make it a prominent part of the medical industry. Deep learning can be used in wide variety of areas like the detection of tumors and lesions in medical images, computer-aided diagnostics, the analysis of electronic health-related data, the planning of treatment and drug intake, environment recognition and brain computer interface , aiming to come up with decision support for the evaluation of the person's health. The key element of the success of deep learning is based on the capability of the neural networks to learn high level abstractions from input raw data through a general purpose learning procedure. Physicians often use chest X-rays to quickly and cheaply diagnose disease associated with the area. However, it is much more difficult to make clinical diagnoses with chest X-rays than with other imaging modalities such as CT or MRI. With computer-aided diagnosis, physicians can make chest X-ray diagnoses more quickly and accurately. Pneumonia is often diagnosed with chest X-Rays and kills around 50,000 people each year. With compute raised diagnosis of pneumonia specifically, physicians can more accurately and efficiently diagnose the disease. In this project, we hope to train a model using the dataset described below to help physicians in making diagnoses of pneumonia in chest X-Rays. Our problem is thus a binary classification where the inputs are chest X-ray images and the output is one of two classes: pneumonia or non-pneumonia.

II. LITERATURE SURVEY

Detecting Pneumonia from Chest X-Ray Images using Committee Machine Shruti Meshram[1], Suhani Thaware[2], Amarendra Kumar Jha[3], Amit Pali[4,] Mayur Khobragade[5], Dr. Virendra K. Taksande[6] B.E. Students[12345], Professor[6] Department of Electronics & Telecommunication Engineering Priyadarshani College of Engineering, Nagpur, Maharashtra, India

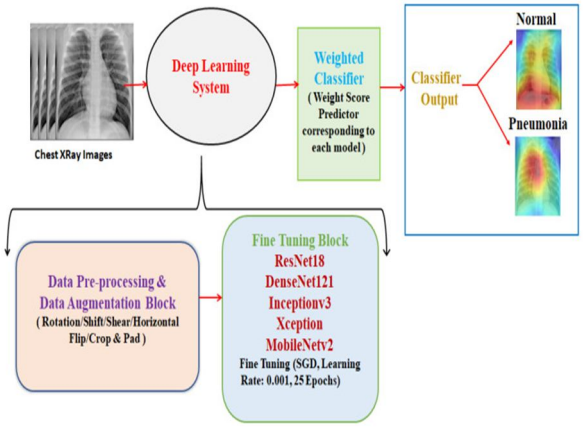
The medical field is the most sensitive of all the domains ever known, for a simple reason that it deals with humans and advances in this field is a matter of pride for the entire human race. The system designed in this research paper is one such attempt. Pneumonia is most important cause of death worldwide even though it is a vaccine preventable disease. It can be detected by analyzing chest x-rays. Analyzing chest x-rays is a difficult task and requires precision. We aim at designing a highly efficient system to predict if a user suffers from Pneumonia by analyzing the patient's chest X-ray images and increasing the accuracy of the system by use of Committee Machine.

©IJRASET: All Rights are Reserved

III. METHODOLOGY

An optimum solution for the detection of pneumonia from chest X-rays is proposed in this paper. Data augmentation was used to address the problem of the limited dataset, and then, state-of-the-art deep learning models, were fine-tuned for pneumonia classification. Then, predictions from these models were combined, using a weighted classifier to compute the final prediction. The complete block diagram of the proposed methodology can be seen in Figure1.

Figure 1. Block diagram of the proposed methodology.



A. Data Preprocessing & Augmentation

Each image had to be preprocessed according to the deep neural network used. There were two important steps involved: resizing and normalization. Different neural networks require images of different sizes according to their defined architecture. ResNet18, DenseNet121, and MobileNetV2 expect images of size 224 × 224, while InceptionV3 and X-ception require images of size 229 × 229. All the images were also normalized according to the respective architectures. Adequate training of a neural net requires big data. With less data availability, parameters are undermined, and learned networks generalize poorly. Data augmentation solves this problem by utilizing existing data more efficiently. It aids in increasing the size of the existing training dataset and helps the model not to over fit this dataset. In this case, there were a total of 1283 images of the normal (healthy) case and 3873 images of the pneumonia case in the training dataset. Out of these, four-hundred images were reserved for optimizing the weighted classifier. This dataset was highly imbalanced. There were already enough images in the pneumonia case. Therefore, each image of only the normal (healthy) case was augmented twice. Finally, after augmentation, there were 3399 healthy chest X-ray images and 3623 pneumonia chest X-ray images. The settings utilized in image augmentation are shown below in Table 1. The images after performing various augmentation techniques are shown below (Figure 2). Only one of these techniques was used to generate the augmented image.

Image: After performing the augmentation technique.

©IJRASET: All Rights are Reserved

TABLE 1.

Augmentation techniques used in the proposed methodology.

Technique	Setting
Rotation	45
Vertical Shift	0.2
Horizontal Shift	0.15
Shear	16
Crop and Pad	0.25

B. Fine-Tuning the Architectures

Raw chest X-ray images, after being pre-processed and normalized, were used to train the network. Then, data augmentation techniques were used to process the dataset more efficiently. All the layers of the networks used were trainable, and these layers extracted the features from the images. It, stochastic gradient descent (SGD) had better generalization than adaptive optimizers. Therefore, SGD as the optimizer was used, and the model was trained for 25 epochs.

C. Weighted Classifier

In this module of the proposed methodology, a weight (Wk.) corresponding to each model was estimated. Wk. can be defined as the belief in the kh model, with *k* being equal to 5 as 5 pre-trained models were used in this paper. Wk. has values between 0 and 1, and the sum of all weights is 1 (Equation (2)). Each model, after it was fine-tuned, returned the probabilities for each class label, i.e., 2 classes in the form of a matrix (Pk). A weighted sum of all these predictions arrays was calculated (Equation (1)).

$$P1W1+P2W2+P3W3+\cdots+PkWk=Pf \quad ...(1)$$

$$W1+W2+W3+\cdots+Wk=1 \quad ...(2)$$

$$Loss=-1N\sum i=1ny\times\log(p)+(1-y)\times\log(1-p) \quad ...(3)$$

Pk is the prediction matrix, with shape: number of optimization images * class labels (400*2), corresponding to each architecture. In Equation (1), the contribution of each model is weighted by a coefficient (Wk.), which indicates the trust in the model. First, we obtained the Pk for every model for an unseen image set (400 images). Then, Equation (1) was optimized such that the classification error was minimized and Equation (2) was also satisfied. We used differential evolution for global optimization of Equation (1). Differential evolution is a stochastic global search algorithm. It optimized Equation (1) by iteratively refining a candidate solution with regard to Equation (2). Hence, optimizing Equation (1) would provide the Wk. values corresponding to each model. The value

©IJRASET: All Rights are Reserved

of Wk. for the kh model depended on the respective models' performance on the test dataset. The maximum iterations for differential evolution algorithms were kept to be 1000. With the help of Pf, the prediction of a class label could be computed. Classification loss corresponding to this Pf was reduced while optimizing Equation (1). Log loss (Equation (3), also known as logistic loss or cross-entropy loss, was used as the loss function. In Equation (3), *N* denotes the size of the image set (400) and *p* denotes the probability that the given image is pneumonia infected. Figure 3 shows the weighted classifier used in the proposed methodology.

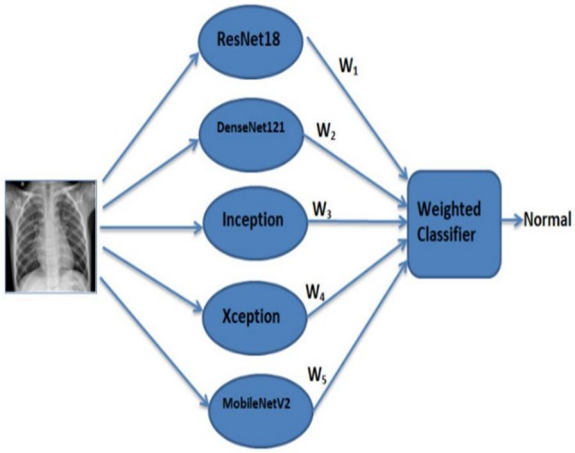


Figure 3.Weighted classifier module used in this paper (weighted predictions from all the models are passed to the weighted classifier, which gives the final weighted prediction).

IV. HARDWARE REQUIREMENT

A desktop/laptop with minimum configuration

- Processor-Pentium(R) 1.74GHz
- RAM-1GB
- Hard disk 128GB

V. SOFTWARE REQUIREMENT

- Browser (chrome/edge/Mozilla Firefox)
- Operating System (windows/ Linux/ mac OS)
- IDE (Integrated Development Environment visual studio code)
- SQLite 3 viewer

VI. FRONTEND LANGUAGES

A. HTML

HTML stands for Hypertext Markup Language. It is used to design the front-end portion of web pages using a markup language. HTML is the combination of Hypertext and Markup language. Hypertext defines the link between the web pages. The markup language is used to define the text documentation within the tag which defines the structure of web pages.

B. CSS

Cascading Style Sheets fondly referred to as CSS is a simply designed language intended to simplify the process of making web pages presentable. CSS allows you to apply styles to web pages. More importantly, CSS enables you to do this independent of the HTML that makes up each web page.

C. JavaScript

JavaScript is a famous scripting language used to create magic on the sites to make the site interactive for the user. It is used to enhancing the functionality of a website to running cool games and web-based software.

©IJRASET: All Rights are Reserved

VII. BACKEND LANGUAGES

A. Python

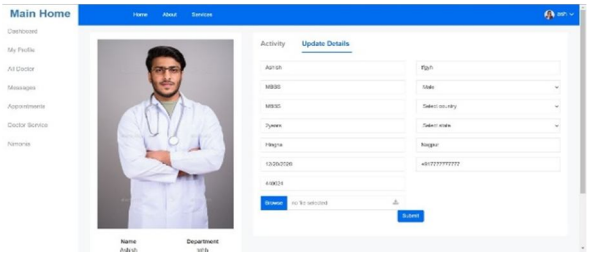
Another language that is being preferred for backend development, specifically in current times, is Python. It is a high-level, general-purpose programming language that supports multiple programming paradigms such as Object-Oriented, Procedural, and Functional. Instagram, Spotify, Google, etc. are some of the popular platforms that are using Python in their tech stacks. The language provides you with some remarkable features such as rich library support, easy integration with other languages, GUI support, compatibility with trending technologies, etc. Also, Python has a very simple syntax and comes up with better code readability aspects that make it easy to learn and use. Popular Python web frameworks are DJANGO, Flask, etc.

B. DJANGO

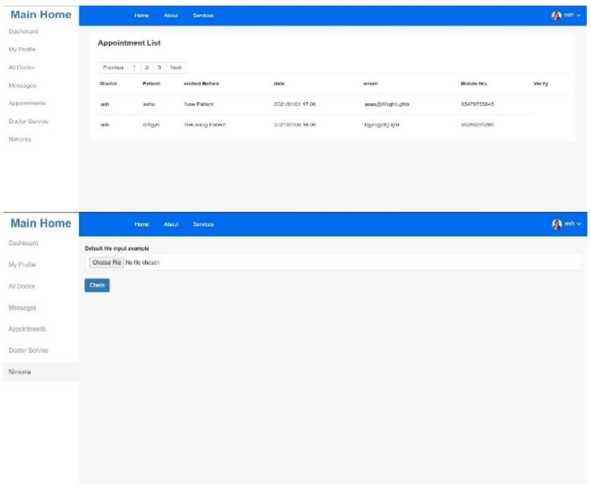
DJANGO is a Python-based open-source web framework that allows you to do web development more efficiently and without any hassle. DJANGO follows the model-template-views (MTV) architectural pattern. The reason behind the immense popularity and demand for this particular framework is some of its noticeable features such as extensibility, rapid development, scalability, security, vast community, and many more. Businesses are using DJANGO for various distinct web development areas such as social networking platforms, scientific computing platforms, content management systems, and various others. Some of the popular website that are using DJANGO are – Instagram, Mozilla, Pinterest, etc.

VIII. WEB APPLICATION

A. Doctor Portal



Here we can add and upload Doctor Details of the respected departments. All the patient who have registered and made an appointment can be seen here in this page under Message section of the portal.

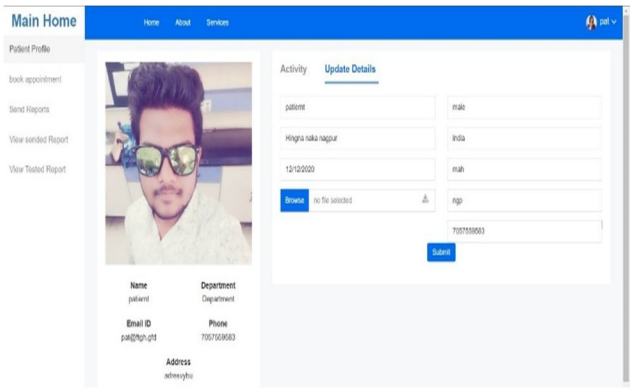


In this section of portal list of available Doctor service can be accessed basically X-Ray service can be used to feed data in our backend software of Machine learning and CNN algorithm.

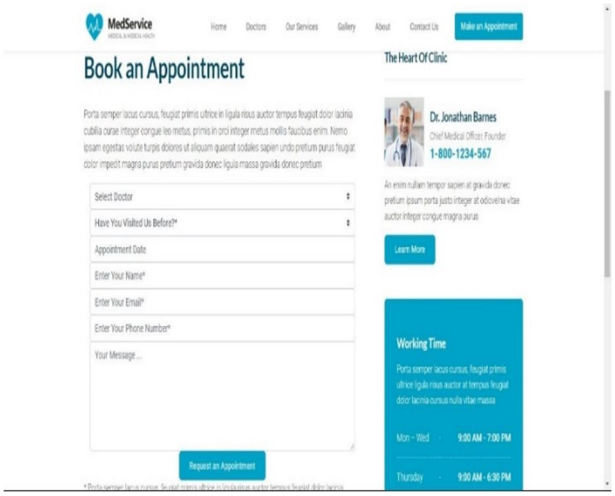
*This portal is linked with Patient portal in **fetch review process and report** model.*

©IJRASET: All Rights are Reserved

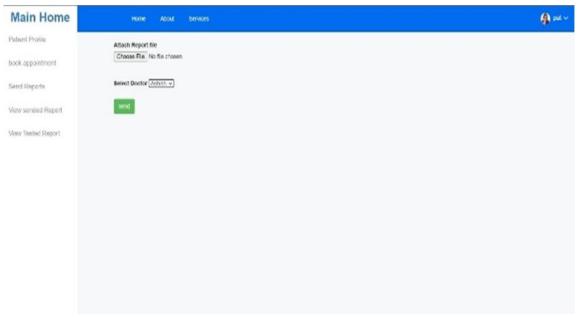
B. Patient Portal



Here Patient can add details and information about themselves to make data available to departments and doctors.



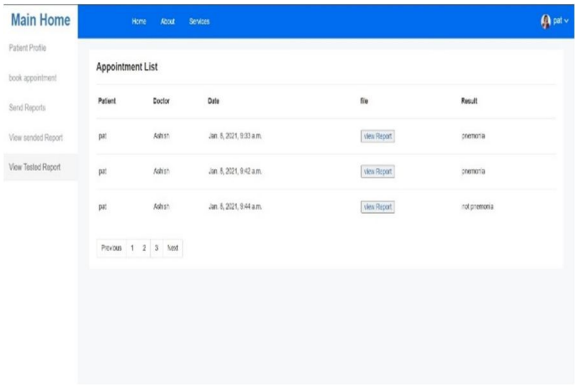
Here Patient can book an appointment for the treatment of their illness. Doctor selection, date of appointment can be chosen according to patient. This can be accessed through Book an appointment section in patient portal.



In this section of page patient will upload digital image of their X-rays to be provided by x-ray department of hospital and the images will be sent to doctor as well as stored.

Here in this section of page patient can view their previously uploaded X-ray report history and can be accessed through View sent report section in Patient Portal. Also In this section of portal patient can view the result of their diagnosis the result is calculated based on success rate of our AI model Machine learning CNN algorithm and verification and approval by assigned doctor in Doctor Approval.

©IJRASET: All Rights are Reserved



Also the previously diagnosed report will be made available to the patient for further diagnosis.

IX. DISCUSSION AND RESULT

Correct diagnostics requires deeper understanding of the radiological features visible in chest X-rays. Unfortunately, deep neural networks are known for providing no explanation as to how the final decision is made. To make the decision support process more useful, the deep network should provide also explanations beyond plain decisions [65]. Such explanations can take the form of semantic segmentation with explanations in natural language assigned to each identified segment of a chest X-ray photo. Correct implementation of such tasks may require the use of additional e-Health data from the patients, and high-quality annotated datasets. Another limitation is introduced by the scarcity of image data representing all types of pneumonia pathologies, which prevents for achieving a higher accuracy or using a deeper network with more parameters. Successful deep learning models such as Alex Net, Google Net and ResNet, have been trained on more than a million images, which are hardly available in the medical domain. Training deep neural networks with limited data available also may lead to over-fitting and prevent from good generalization.

The accuracy results reached in this paper could be still improved by adding more sophisticated deep networks to the ensemble and training the networks with a larger dataset. Future research directions will include the exploration of image data augmentation techniques [66] to improve accuracy even more, while avoiding over fitting.

X. FUTURE SCOPE

Pneumonia constitutes a significant cause of morbidity and mortality. It accounts for a considerable number of adult hospital admissions, and a significant number of those patients ultimately die (with a mortality rate of 24.8% for patients over 75 years). According to the WHO, pneumonia can be prevented with a simple intervention and early diagnosis and treatment. Nevertheless, the majority of the global population lacks access to radiology diagnostics. Even when there is the availability of imaging equipment, there is a shortage of experts who can examine X-rays. Through this paper, the automatic detection of pneumonia in chest X-ray images using deep transfer learning techniques was proposed. The deep networks, which were used in our methodology, had more complex structures, but fewer parameters and, hence, required less computation power, but achieved higher accuracy. Transfer learning and data augmentation were used to solve the problem of over fitting, which is seen when there is insufficient training data, as in the case of medical image processing. Further, to combine different architectures efficiently, a weighted classifier was proposed. The experiments were performed, and the different scores obtained, such as the accuracy, recall, precision, and AUC score, proved the robustness of the model. The proposed model was able to achieve an accuracy of 98.857%, and further, a high F1 score of 99.002 and AUC score of 99.809 affirmed the efficacy of the proposed model. Though many methods have been developed to work on this dataset, the proposed methodology achieved better results. In the future, it would be interesting to see approaches in which the weights corresponding to different models can be estimated more efficiently and a model that takes into account the patient's history while making predictions.

XI. CONCLUSION

In this article, our goal is to propose a deep learning-based approach to classify pneumonia from chest X-ray images using transfer learning. In this framework, we adopted the transfer learning approach and used the pre-trained architectures, Alex Net, DenseNet121, Inception V3, Google Net and ResNet18 trained on the Image Net dataset, to extract features. These features were passed to the classifiers of respective models, and the output was collected from individual architectures. Finally, we employed an ensemble model that used all five pre-trained models and outperformed all other models. We observed that performance could be

©IJRASET: All Rights are Reserved

improved further, by increasing dataset size, using a data augmentation approach, and by using hand-crafted features, in future. Our findings support the notion that deep learning methods can be used to simplify the diagnostic process and improve disease management. While pneumonia diagnoses are commonly confirmed by a single doctor, allowing for the possibility of error, deep learning methods can be regarded as a two-way confirmation system. In this case, the decision support system provides a diagnosis based on chest X-ray images, which can then be confirmed by the attending physician, drastically minimizing both human and computer error. Our results suggest that deep learning methods can be used to improve diagnosis relative to traditional methods, which may improve the quality of treatment. When compared with the previous state-of-the-art methods, our approach can effectively detect the inflammatory region in chest X-ray images of children.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

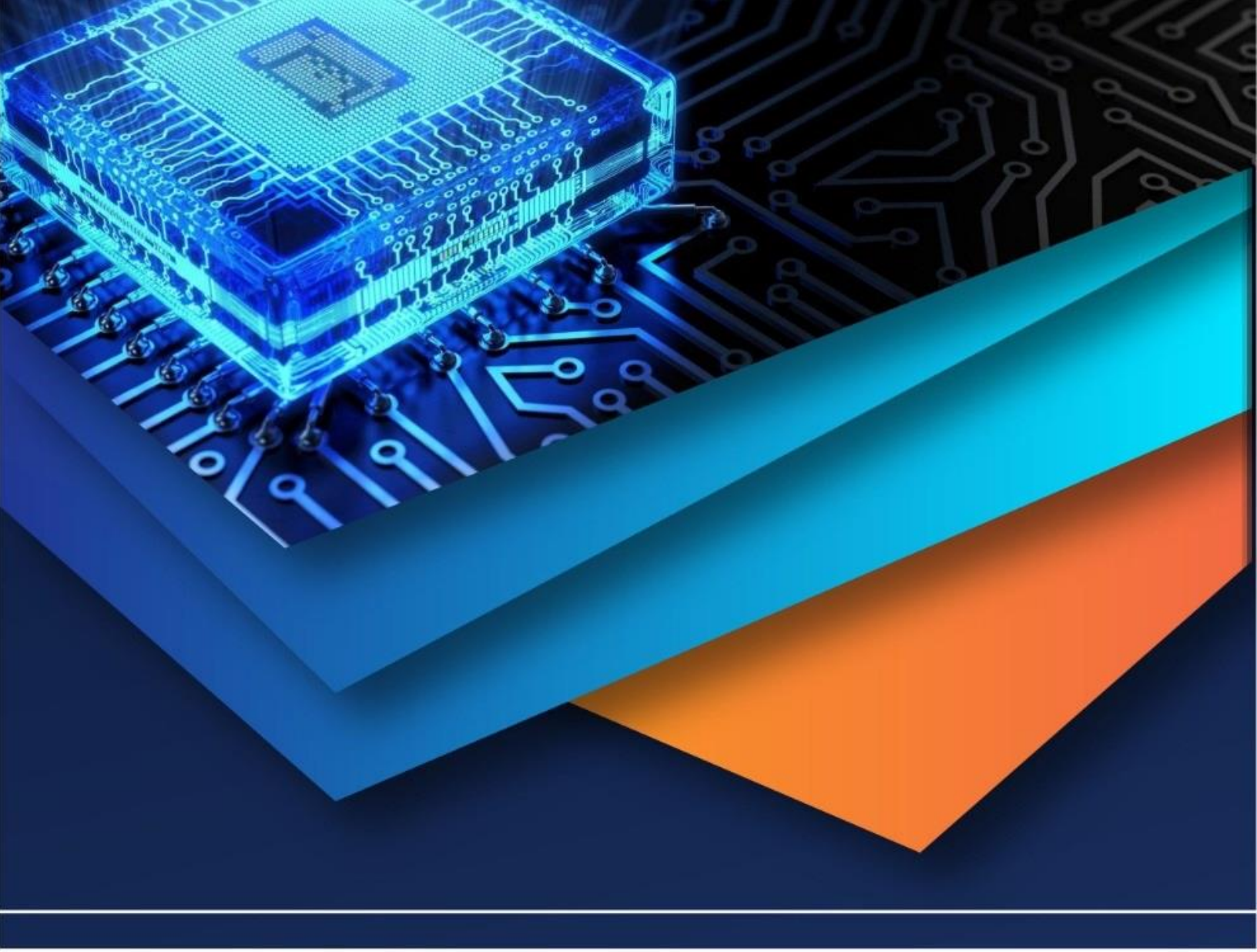
XII. ACKNOWLEDGEMENT

We would like to express our sincere appreciation, and respect to our supervisor Dr. Virendra K. Taksande, Professor of Department of Electronic & telecommunication Engineering, Rashtrasant Tukadoji Maharaj Nagpur University. Throughout the year Dr. Virendra K. Taksande has not only given us technical guidelines, advice to complete the work, but also Dr. Virendra K. Taksande has given us continuous encouragement. His continuous support was one of the most successful ingredients that helped us to achieve our result. Without his sincere care, this work not has been materialized in the final form that it is now at the present.

REFERENCES

[1] M. Aydogdu , E. Ozyilmaz , H. Aksoy , G. Gursel , and N. Ekim , "Mortality prediction in community-acquired pneumonia requiring mechanical ventilation; values of pneumonia and intensive care unit severity scores," Tuberk Toraks, vol. 58, pp. 25-34, 2010.
[2] W. H. Organization, "Standardization of interpretation of chest radiographs for the diagnosis of pneumonia in children," World Health Organization 2001.
[3] M. I. Neuman, E. Y. Lee, S. Bixby, S. Diperna, J. Hellinger, R. Markowitz, et al., "Variability in the interpretation of chest radiographs for the diagnosis of pneumonia in children," Journal of hospital medicine, vol. 7, pp. 294-298, 2012.
[4] W. H. Organization, "Standardization of interpretation of chest radiographs for the diagnosis of pneumonia in children," World Health Organization 2001.
[5] M. I. Neuman, E. Y. Lee, S. Bixby, S. Diperna, J. Hellinger, R. Markowitz, et al., "Variability in the interpretation of chest radiographs for the diagnosis of pneumonia in children," Journal of hospital medicine, vol. 7, pp. 294-298, 2012.
[6] H. D. Davies, E. E.-L. WANG, D. Manson, P. Babyn, and B. Shuckett, "Reliability of the chest radiograph in the diagnosis of lower respiratory infections in young children," The Pediatric infectious disease journal, vol. 15, pp. 600-604, 1996.
[7] R. Hopstaken, T. Witbraad, J. Van Engelshoven, and G. Dinant, "Inter-observer variation in the interpretation of chest radiographs for pneumonia in community-acquired lower respiratory tract infections," Clinical radiology, vol. 59, pp. 743-752, 2004.

©IJRASET: All Rights are Reserved



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 (24*7 Support on Whatsapp)