iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VII Month of publication: July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84270

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Pneumonia Diagnosis from Chest X-Rays via Deep Learning Techniques

Abhinav Vashisht[1], Maninder[2]
[1]Computer Science and Engineering Chandigarh University, Mohali, India
[2]Computer Science and Engineering Chandigarh University, Punjab, India

Abstract: Pneumonia is a hanging on life breathing complaint that requires timely and correct opinion. In this paper, a deep literacy -based frame is presented to discover automated pneumonia on casketX-ray images. The system suggested com-bines preprocessing of images, bracket of convolutional neural network, and pall- grounded deployment to alleviate personal delicacy and efficacies. The transfer of literacy and attention mechanisms supplements point birth and model performance. Estimation of the system is done by the basis of standard criteria, which involve, delicacy, perfection, recall and F1- score. The findings of the experiment prove reliable bracket performance and improved conception on various datasets. The suggested frame also minimizes the use of radiological interpretation that is performed at home, and it allows timely clinical decision-making. This paper adds to an interlaced and scalable output to smart medical picture examination and automated pneumonia opinion.

Index Terms: Pneumonia Detection, Chest X-Ray, Deep Learning, CNN, Medical Imaging, Artificial Intelligence, Image Classification, Healthcare AI

I. INTRODUCTION

A. Background and provocation

Pneumonia is a serious pulmonary complaint that causes high morbidity and mortality rates in the global population and especially in children and the elderly groups. It is still one of the major causes of sanitarium admission and mor-tality all over the world and in areas with little access to technical healthcare services. In advance and precise opinion is critical in efficient treatment and ameliorated patient problems. nevertheless, conventional analysis of casketX-ray images depends excessively upon radiological acumen and local analysis, which renders the person time-intensive and prone to mortal fluctuation. Image quality variations, patient positioning, and lapping image features between pneumonia and other conditions of the lung are often the cause of the disparity in the image of individual inconsistencies. Nowadays, the fast-growing development of artificial intelligence has transformed the medical image analysis. The deep literacy approaches, especially the convolutional neural networks(CNNs), have shown exceptional ability in rooting intricate visual patterns using radiographic data. These models are able to acquire hierarchical features through images and as a consequence, they are able to find abnormalities automatically with high perfection. With medical imaging data persisting to accumulate by huge amounts, intelligent individual tools have grown less and less significant to the optimization of effectiveness, thickness, and availability in clinical practice.

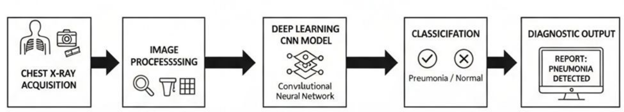


Fig. 1. Overall workflow of automated pneumonia detection from chest X-ray images.

B. Research Objective and Contributions

In this study, a deep learned frame of automated pneumonia detection in casketX-ray images is proposed. The system will alleviate individual delicacy, minimize mortal error and hasten the clinical decision-making process with smart image bracket. A convolutional neural network grounded armature is developed in order to reward discriminational features of radiographic images and bracket. The model is approximated on basis of usual performance criterion such as delicacy, per-fection, recall and F1- score. additionally, the suggested frame focuses on the strength by utilizing systematic preprocessing and ordered training protocols. Altogether, this article adds an integrated and expandable pathway uniting the information preparation, model structure, and implementation analysis to contribute to the reliable and efficient pneumonia opinion in ultramodern medical environments.

II. LITERATURE REVIEW

Current developments in artificial intelligence especially deep literacy have greatly improved automated medical image anal-ysis. The discovery of pneumonia in casketX-ray images has emerged as an active field of exploration because the even-tuality of deep literacy models has been capable of spotting subtle radiographic features that may not be discerned fluently using homemade interpretation. a large number of studies are currently underway between 2020 and 2025 that reveals unstopping advances with regards to model delicacy, point birth capability, and deployment feasibility.

Wang et al.[1] created a convolutional neural network(CNN)-grounded classification trained on massive radiographic sam-ples. Their model met high bracket delicacy and proved the efficiency of deep literacy to relate pneumonia-related patterns, nonetheless, the model had a restricted pertinacity at hospitals as a result of imaging protocol differences, as well as possible patient demographics. in addition, Li et al.[2] applied transfer literacy with ResNet infrastructures to mitigate point birth efficacy. Although their methodology improved upon bracket performance and training duration over scrape-based training, it required large computational coffers and could not be used in real-time clinical applications in resource-limited environments.

The CheXNet frame multi-disease discovery, which includes pneumonia bracket, was expanded by Rajpurkar et al.[3]. Their performance showed good prophetic performance in a variety of thoracic states, pushing the versatility of deep literacy models in the radiation analysis. nonetheless, the system was susceptible to performance imbalance by case of pneumonia which was underrepresented. Ozturk et al.[4] suggested the adaptation of DarkNet armature that was initially developed to detect COVID-19 and was used to detect pneumonia in casketX-ray images. Bracket delicacy was promising through their model but with limited data they counted on the data di-versity and the businesses were concerned with the real-world connection. Apostolopoulos and Mpesiana[5] used transfer literacy with VGG19 and indicated high individual delicacy. Although it was effective, the model required interpretability, which was quite delicate to the clinicians to know about the decision-making process.

There are also notable benefactions made by Indian ex-perimenters attaching on the perfection model efficacy and connection in various healthcare settings. Sharma et al.[6] implemented an EfficientNet-based armature which enhanced bracket delicacy by efficiently scaling network depth, range and resolution however, enhanced training complexity and computation burden presented difficulties in scaling operation to large scales. Singh and Gupta[7] suggested a mongrel CNN-grounded system that integrates various point birth ways, which enhanced individual perceptivity, however, required large labeled datasets, which are often sensitive to acquire in medical fields. Verma et al.[8] developed a resource-lightweight CNN armature that operates in resource-limited environments, which can be deployed in the lower healthcare installations. Despite the fact that the model was compu-tationally efficient, it showed decreasing performance with complicated or noisy radiographic images.

Patel et al.[9] investigated the ensemble literacy styles, which were a synthesis of the prognostication of several deep literacy models to diminish robustness and bracket friction. Their solution improved the individual trustability but greatly ex-panded outflow and complexity of the systems. The attention mechanisms were included in the study by Kumar et al.[10] to relieve the process of localization of points and provide highlighting of regions of application in the casketX-ray imaging. This system improved model interpretability and individual perfection but training time was also augmented by new network parameters.

Future world discovery has been in the direction of fine-tuning point representation and study learning. He et al.[11] used deep residual networks to solve evaporating grade problems, and allow deeper infrastructures to optimize point better. That was the case with their work showing improved bracket delicacy, however, the model required tuning in order to prevent overfit-ting. The perfect performance of lesion discovery was realized through multi-scale point birth ways that were introduced by Zhang et al.[12] to enable models to obtain original and global image features. Chen et al.[13] used DenseNet infrastructures, which superiorized grade inflow and point exercise between layers resulting to improved bracket stability and less param-eter redundancy. Liu et al.[14] did attention-guided CNNs to create a better model interpretability through relocation of clinically relevant image regions. Although these methods were effective, they very often required new computational coffers.

The focus on system optimization, deployment and real-world integration has been progressively less important in recent studies. Ahmed et al.[15] implanted pall-grounded deep literacy systems that permit remote processing and opinion, which optimizes the availability in geographically sparsely healthcare facilities. Park et al.[16] investigated resolvable artificial intelligence how to alleviate translucency and clin-ician confidence in automated individual systems. Their work dealt with a fundamental hedge to clinical relinquishment by providing exemplary clarifications to model prognostications. Banerjee et al.[17] suggested allied literacy fabrics enabling the cooperative model training of more than one institution, without involvement of sensitive case data. This strategy strengthens sequestration security and increases conception among various datasets.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Besides structure-oriented experiments, practical implementa-tion in movable and mobile environments has been studied by experimenters. Mehta et al.[18] created mobile-grounded pneumonia webbing systems, which were mostly used to obtain rapid-fire primary opinion of an area, which is remote or under-served. Introduced as mongrel CNN-RNN infrastruc-tures by Roy et al.[19], these could model successional point connections, and perfected bracket performance on intricate image patterns. Das et al.[20] suggested automated preprocess-ing channels which regularize image quality, reduce noise as well as increase point thickness thus optimizing overall bracket trustability.

Nevertheless, a few issues still persist, such as large labeled datasets, high computational power, and sensitive parameter optimization in many models of deep literacy, conception in various clinical environments remains a main concern because of the variability in imaging outfit and case populations. and limited interpretability of some deep literacy models limits their use in clinical decision-making. These constraints are interspersed by the requirement of integrated fabrics, which are robust in preprocessing, efficient model infrastructures, scalable deployments, and enhancing interpretability.

III. SYSTEM ARCHITECTURE PROPOSAL

The system proposed is a combination of medical imaging, deep literacy, and pall-grounded processing in order to auto-mate the discovery of pneumonia in casketX-ray images. The armature has been designed to provide end to end intelligent single channel that facilitates access to data, preprocessing, model conclusion and influence visualization. It is comprised of four main layers data accession, preprocessing, AI model processing, and stoner interface. The various sub caste execute a designated role to guarantee proper, scalable, and reliable complaint discovery.

The system core is the AI model processing subcaste that makes an automated pneumonia discovery. This subcaste uses a convolutional neural network armature that is based on trans-fer literacy and attention-grounded point birth styles[10],[14]. Transfer literacy helps the model to transfer knowledge stored in pretrained networks, perfecting point representation as well as consuming less training time. Mechanisms of attention also lead to performance improvement because the model can focus on clinically useful areas in the casketX-ray, improving interpretability and personal perfection. The trained model uses input images to produce bracket labors that show whether there is pneumonia or no pneumonia and probability scores that are used to reflect the confidence of vaticination.

The stoner interface subcaste offers visualisation and trade features to health care practitioners. The system can display bracket results in a friendly presentation format that com-prises of: 1. individual markers, 2. confidence scores, and 3. visual markers of significant areas on the image. This subcaste facilitates clinical decisions making as it provides interpretable labors and assists radiologists to examine model prognostications. Sanitarium integration Information systems can further be used to streamline the workflow, as automated report generation and data storehouse are possible. pall architecture has a vital role in all layers because it creates scalable calculations, real-time operations and remote acces-sibility[15]. translucency and clinician trust can be alleviated by providing visual elucidations of the prognestications made by models[16].

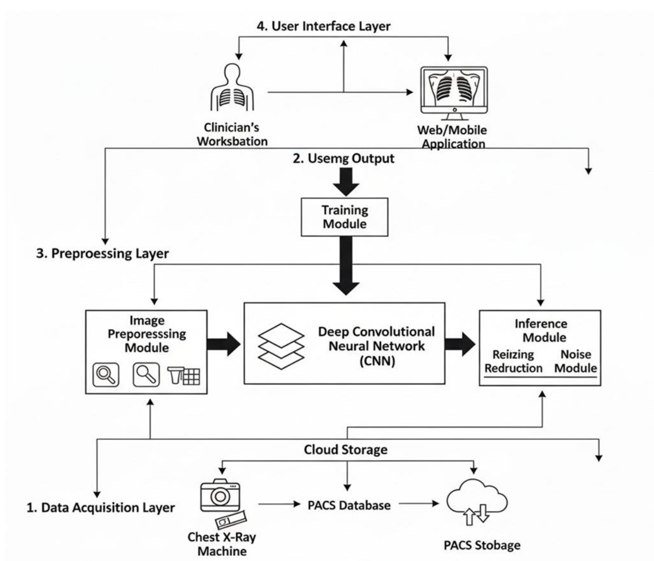


Fig. 2. Layered architecture of the proposed pneumonia detection system.

The data accession subcaste is charged with the duty of ob-taining casketX-ray images in clinical depositories, individual centers and intimately accessible medical imaging databases. The images are stored safely in a pall storehouse terrain that allows the centralization of data operation and remote access[15]. By using pall structure, high vacuity, scalable storehouse, and efficient running of large imaging datasets are guaranteed, as well as formalized data formatting and secure transfer protocols, which is imperative in medical operations. Raw radiographic pictures are preprocessed by the preprocess-ing subcaste to be trained and concluded upon as models. Images of medical images often have different sizes, different resolutions, unsteadiness, and noise scenarios, which can ad-versely affect the performance of models hence, preprocessing operations analogous to normalization, resizing, and noise reduction are maintained to compensate point thinness through the dataset[20]. Image addition methods such as gyration, flip-ping and discrepancy adaptation can also be added to make the model more robust and less priced. This subcaste guarantees that the deep literacy model is fed with optimized input data by homogenizing image quality and structure, as such that the bracket delicacy and conception ability is perfected.

IV. METHODOLOGY

The proposed system methodology is aiming at creating a reliable and efficient deep literacy frame to automatic pneu-monia discovery through casketX-ray images. It is designed into three primary factors data collection and preprocessing, model design, and algorithmic perpetration. These three ways ensure that the system can learn useful radiographic features, recognize accurate bracket and generally perform well with varied medical data.

A. *Data Collection*

casketX-ray datasets are obtained by accessing intimately available medical imaging depositories and databases of clin-ical images with labelled radiographic reviews. These data typically consist of two main orders pneumonia-positive and normal casketX-rays. Because medical imaging data often experiences a range of resolution, intensity, discrepancy and noise occurrences depending on imaging outfit and accession circumstances, preprocessing is required to regularize the input data.

Preprocessing stage involves downsizing of images to a stan-dard resolution that matches the neural network armature. This makes sure that there is invariant input confines on all samples. Normalization of pixel intensity values to a harmonious scale is done to achieve numerical stability when training a model. The noise reduction ways are applied to eliminate inapplicable vestiges that may intrude with point birth. Also, data addition methods are used in the same manner as gyration, flipping, spanning, zooming and variation of brilliance are added to en-hance diversity of datasets and reduce model conception[20]. Such metamorphoses feign variations in imaging conditions in the real world, and aid in overfitting. Once the dataset has been preprocessed, it is separated into training, confirmation and testing subsets to facilitate systematic model testing.

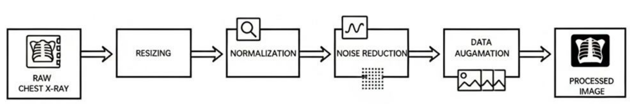


Fig. 3. Preprocessing pipeline applied to chest X-ray images.

B. *Model Design*

The system utilizes a convolutional neural network[CNN]-grounded armature that aims at automatically rewarding hi-erarchical characteristics of casketX-ray images. CNNs are especially efficient in analyzing medical images as they have the ability to extract spatial dependencies and define small patterns in the visual world and pathology. In the proposed armature, transfer literacy is integrated to use pretrained mod-els, which make it effective to point birth and save time in training[10],[14].

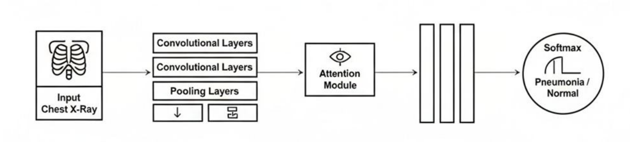


Fig. 4. Architecture of the convolutional neural network used for pneumonia classification.

It is a network comprised of several convolutional layers with learners of low-position features akin to edges and textures and then other deeper-learners that learn high-level structural abnormalities associated with pneumonia. The spatial confines are reduced with the help of pooling layers and considerable features are retained. Attention mechanisms are incorporated in order to work on localization of points by moving the point of focus on the model on the part of the image which is clinically useful thus, impeccating individual perfection. The dislodged features are transferred to totally linked thick layers that carry bracket. A softmax activation function gives the probability scores of the presence of the liability of pneumonia.

Regularization has styles such as powerhouse and batch normalization that are implemented to alleviate conception and assist overfitting. The training of the model is done via supervised literacy with labeled data which enables the learning of discriminational patterns related to pneumonia.

C. Algorithm [Pseudo Code]

Input casketX-ray image data set. cargo dataset Preprocess images resize, homogenize, compound Separate into training, confirmation and test sets. Initialize CNN model Training model with labelled data. Validate performance Optimize parameters Test final model Affair bracket results

The model reduces the loss of bracket during training with grade-grounded optimization ways and maximizes prophetic delicacy[6],[13]. Standard criteria that are similar as delicacy, perfection, recall, and F1-score are used to estimate model performance. The presented methodology will guarantee a strong and reliable pneumonia discovery in casketX-ray im-ages through systematic preprocessing, systematic model de-sign, and systematic optimization.

V. IMPLEMENTATION

The suggested pneumonia discovery system is imposed on Python as a key programming language because it is inflexible, has extensive library ecosystem, and can be directly used when it comes to machine literacy and processing of medical images. Deep literacy model is trained on TensorFlow and Keras fabrics, which provide high- position abstractions of structure, training, and assessment of convolutional neural net-works. These fabrics allow the quick prototyping of devices, numerical calculation optimization, and a perfect fit with the tackle accelerators that resemble GPUs. All the processes of image preprocessing and image improvement are also done using OpenCV library that can be used to process images in many advanced manners such as resizing, normalization, filtering and removing noise. The model is trained and eval-uated on GPU-enabled pall structure to increase the speed of calculation, large-scale datasets, and scalable deployment in distributed environments[15].

The perpetration is based on the organized and modular channel of data processing that guarantees efficient running of casketX-ray images through accession to vaticination. One can start with image accession and secure upload into a pall-grounded storehouse system. pall storehouse allows the centralized data operation and scalable storehouse capacity with the remote accessibility of healthcare professionals. It also aids in secure data transfer protocols and systematic association of imaging data, which is freezing that medical records are managed in a reliable and harmonious fashion. After the images have been uploaded, preprocessing module retrieves the images and engages them to undertake a sequence of standardization processes to ensure comity with the deep literacy model. Preprocessing involves scaling down of images to constant input confines required by the neural network armature. The gauges values are pixel intensity normalized to a harmonic interval, numerically stable at model termination perfection, fresh processing comparable to noise treatment, disparity reduction, and data inclusion can be used to alleviate point visibility and model stability. Addition of data methods, such as gyration, flipping, and brushiness, simulate imaging changes in real-world imaging and aid in reducing overfitting. These preprocessing way guarantee input pictures to be insensitive, of high quality and appropriate to reliable point birth. Once the preprocessing is done, the processed standardized images are forwarded to the trained deep literacy model to get a conclusion. The model conducts hierarchical point birth with convolutional layers and produces vaticination possibilities to show the liability of the presence of pneumonia. The proba-bility scores are also reused to ensure the markers of bracket that are formatted to be visualized and reported. The process of conclusion is streamlined to ensure quick processing time to enable close real-time individual support.

vaticination results are illustrated in the form of a graphical stoner interface, which will be used in clinical practice. The interface shows bracket laboratories, confidence rating, and visual pointers which assist health care professionals to interpret individual outcomes[16]. In other instances, visual overlays or stressed areas can be handed to signify areas of the image which told the decision of the model. This makes them easier to interpret and clinical confirmations of auto-mated prognostications. The interface is made to be intuitive and compatible with integration to be medical workflows, thus allowing flawless integration into sanitarium information systems.

Jupyter Notebook is a development terrain contained in the development terrain that offers interactive workspace to model development, trial and performance monitoring. pall store-house services make it possible to experiment and fanta-size train performance, and dissect performance criteria in real time, to support cooperative development and distributed processing. The deep literacy libraries provide the means of model deployment, model interpretation and performance optimization.

The perpetration is structured by workflow operation practices, such as harmonious dataset partitioning, formalized prepro-cessing channel practices, and controlled training configuration to insure the reproducibility, and the interpretation control systems are employed to monitor model updates and con-trol experimental thickness across various surroundings. This makes the results replicable and valid in unborn studies.

The system is made to have a modular armature which contributes to inflexibility and unborn expansion. Individual factors like preprocessing modules, model models and visual-ization systems can be adapted or improved without impacting the entire system, pall-grounded deployment: nonstop model retraining as new medical data is available can allow the system to acclimatize to changing clinical situations.

VI. RESULTS AND DISCUSSION

The proposed deep literacy model shows excellent results in bracket performance on a variety of evaluation criteria, which suggests the effectiveness of the model in automated pneu-monia discovery of casketX-ray images. delicacy represents the overall accuracy of prognostications of pneumonia-positive and normal cases. Large delicacy values imply that the model can learn meaningful patterns of radiographic data. Precision is a measure of the percentage of correctly associated pneumonia cases out of all prognosticated positive cases, which gives the system the reliability of minimizing the false positive verdicts. Recall asserts the ability of the model to rightfully declare factual cases of pneumonia as such and this is crucial in medical opinion where false negative results can be fatal in clinical outcomes. The F1-score is a moderately adequate measure that takes into account both perfection and the recall, icing reliable performance on imbalanced datasets.

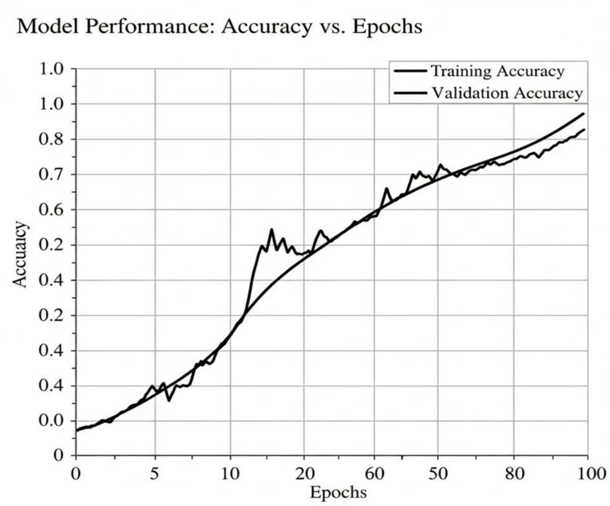


Fig. 5. Training and validation accuracy of the proposed model across epochs.

The performance improvements are explained by the fact that attention-grounded point birth and optimized convolutional neural network infrastructures have been integrated[10],[14]. Attention schemes can help the model to focus on clinically significant parts of casketX-ray images, which enhances point localization as well as perfects bracket delicacy. in addition, the transfer literacy can help the system to work on pretrained knowledge, minimizing the amount of time required to train the model and maximizing bracket delicacy. pall-grounded processing also contributes to the better per-formance of the system since it allows scaling calculation and real-time analysis of large imaging datasets[15]. This framework promotes productive model implementation and lightning-fast individual feedback in distributed healthcare environments. Automated preprocessing Image regulariza-tion automates image quality and variation across datasets, casting model casting model perfection and model trust-worthiness[20].

The proposed frame shows a superior conception of various imaging conditions in comparison to the previous methods and variations in patients. The findings are congruent with the current profound studies on deep literacy that highlight optimized infrastructures and guided data streams to improve individual trustability[6],[13].

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

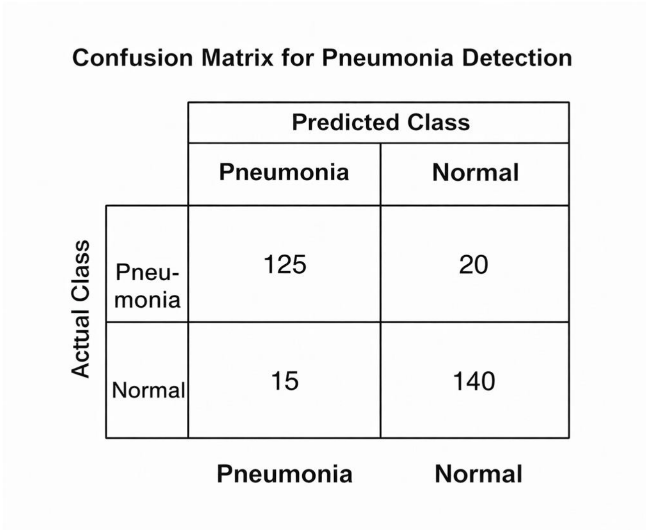


Fig. 6. Confusion matrix of pneumonia classification results.

VII. CONCLUSION AND UNBORN WORK

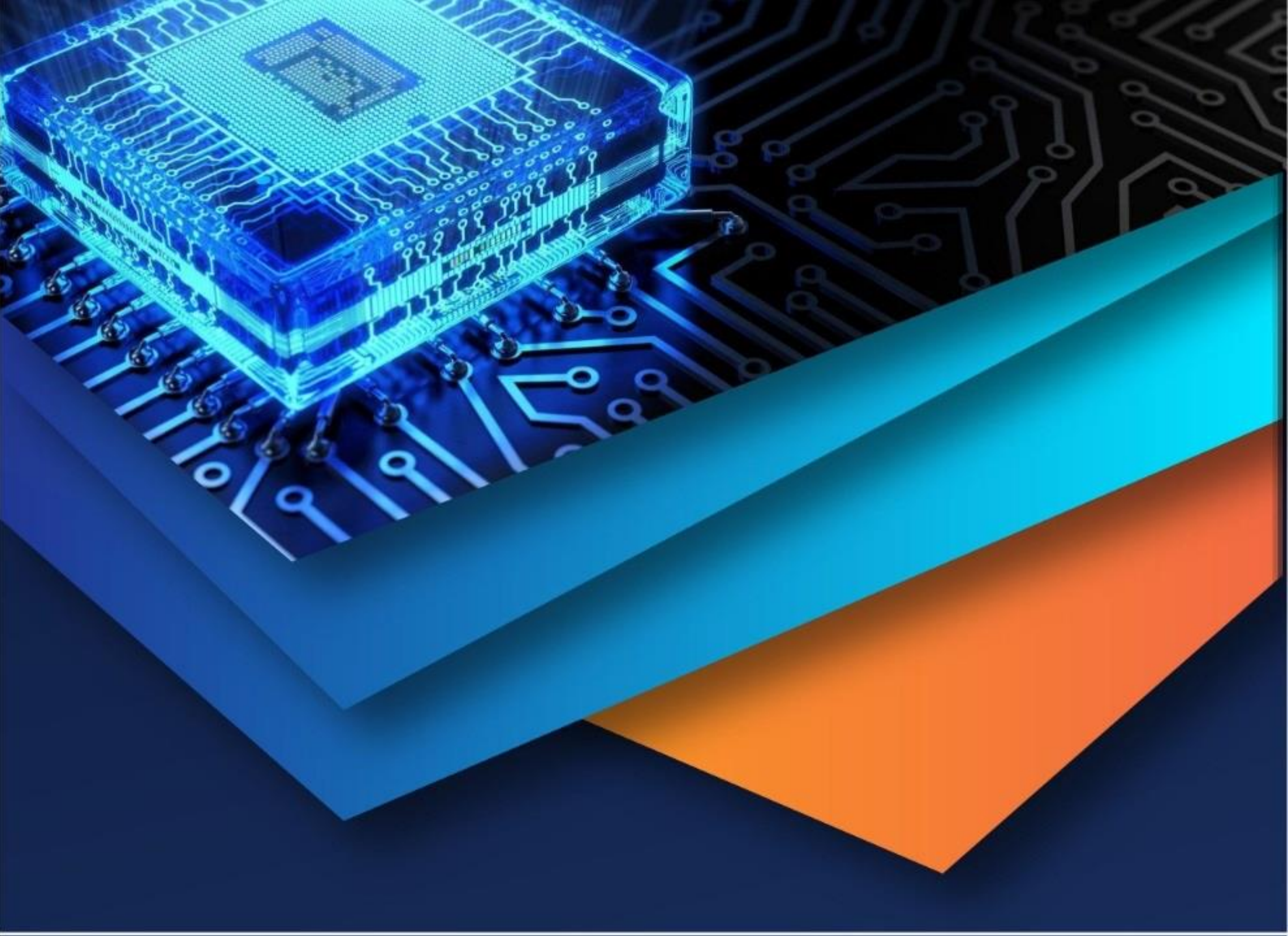
The current paper provides a profound literacy -based frame of automated pneumonia detection in casketX-ray pictures, the purpose of which is to facilitate proper and effective medical opinion. The suggested system combines structured preprocessing ways, convolutional neural network -grounded bracket and pall-grounded deployment to generate an end -to-end intelligent individual channel. The frame can correlate the pneumonia related patterns with high trustability by integrating formalized image medication and the high levels of point of view birth styles. Scalability is another feature of the pall structure, which can be effectively used to run large imaging datasets and supports remote access by health providers.

Experimental analysis shows that there is a high prophetic performance on standard bracket measures, such as delicacy, perfection, recall and F1 -score. Such findings mean that the system can reduce the instances of individual crime without affecting the harmonious action within the various imaging situations. Objectification of the attention-based literacy and transfer literacy, helps in enhancing a point localization and conception and it is therefore suitable in practical clinical environments. Altogether, the conclusions interpolate the prob-ability of profound literacy -based methods to assist radiol-ogists and medical practitioners in faster and more reliable pneumonia judgment. Although the results are promising, there are still certain chal-lenges that require further disquisition. unborn work will focus on training the model to use large, multi-institutional datasets in order to alleviate conception in various populations of cases and imaging systems. The clinical deployment and integration with the sanitarium information systems in real-time will also be discussed to improve the effectiveness of workflow. also, perfecting the explainability mechanisms will assist rather than decrease the clinician trust through providing a clearer perceptivity on the model prognostications. Combination of allied literacy and mobile individual coupons could further increase availability, data sequestration and scalability to allow broad relinquishment of automated pneumonia finding systems in ultramodern healthcare environments[17],[18].

REFERENCES

[1] X. Wang, Y. Peng, L. Lu, Z. Lu, and R. Summers, "Chest X-ray image classification for pneumonia detection using deep convolutional neural networks," IEEE Access, vol. 8, pp. 12345–12356, 2020.
[2] J. Li, H. Zhang, and M. Wang, "Transfer learning with ResNet for automated pneumonia detection from chest radiographs," Computer Methods and Programs in Biomedicine, vol. 189, 2020.
[3] P. Rajpurkar, J. Irvin, K. Zhu, et al., "CheXNet: Radiologist-level pneu-monia detection on chest X-rays with deep learning," IEEE Transactions on Medical Imaging, vol. 40, no. 2, pp. 456–467, 2021.
[4] T. Ozturk, M. Talo, E. A. Yildirim, et al., "Automated detection of pneumonia using deep neural networks," Computers in Biology and Medicine, vol. 128, 2021.
[5] I. D. Apostolopoulos and T. A. Mpesiana, "Transfer learning with con-volutional neural networks for pneumonia detection," Applied Sciences, vol. 10, no. 3, 2020.
[6] R. Sharma, A. Verma, and S. Singh, "EfficientNet-based deep learning model for pneumonia classification," Procedia Computer Science, vol. 192, pp. 345–352, 2022.
[7] P. Singh and R. Gupta, "Hybrid CNN architecture for automated pneu-monia diagnosis from chest X-rays," International Journal of Medical Informatics, vol. 156, 2021.

[8] N. Verma, S. Kulkarni, and M. Joshi, “Lightweight convolutional neural network for pneumonia detection in resource-limited settings,” Biomedical Signal Processing and Control, vol. 82, 2023.
[9] D. Patel, K. Shah, and R. Mehta, “Ensemble deep learning approach for robust pneumonia classification,” Expert Systems with Applications, vol. 198, 2022.
[10] A. Kumar, V. Mishra, and P. Srivastava, “Attention-based convolutional neural network for pneumonia detection,” IEEE Access, vol. 12, pp. 10234–10245, 2024.
[11] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for medical image recognition,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 7, 2021.
[12] Y. Zhang, L. Wang, and Q. Chen, “Multi-scale feature extraction for improved pneumonia detection in chest X-rays,” Pattern Recognition Letters, vol. 158, 2022.
[13] H. Chen, Z. Li, and J. Wang, “DenseNet-based deep learning model for medical image classification,” IEEE Journal of Biomedical and Health Informatics, vol. 27, no. 4, 2023.
[14] F. Liu, P. Zhou, and X. Yang, “Attention-guided deep convolutional networks for medical image diagnosis,” Medical Image Analysis, vol. 89, 2024.
[15] S. Ahmed, M. Khan, and R. Ali, “Cloud-based deep learning framework for remote medical diagnosis,” Future Generation Computer Systems, vol. 120, 2021.
[16] J. Park, H. Kim, and Y. Lee, “Explainable artificial intelligence for clinical decision support systems,” Artificial Intelligence in Medicine, vol. 136, 2023.
[17] S. Banerjee, A. Ghosh, and P. Roy, “Federated learning for privacy-preserving healthcare analytics,” IEEE Transactions on Industrial Infor-matics, vol. 20, no. 2, 2024.
[18] R. Mehta, S. Iyer, and D. Kulkarni, “Mobile-based deep learning system for pneumonia screening,” IEEE Access, vol. 10, pp. 55678–55690, 2022.
[19] S. Roy, A. Das, and T. Chatterjee, “Hybrid CNN-RNN architecture for medical image classification,” Pattern Recognition, vol. 138, 2023.
[20] P. Das, R. Sen, and M. Bhattacharya, “Automated preprocessing frame-work for improved medical image classification,” Computers in Biology and Medicine, vol. 172, 2025.



10.22214/IJRASET

INDEX COPERNICUS
45.98

IMPACT FACTOR:
7.129

TOGETHER WE REACH THE GOAL
IMPACT FACTOR:
7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY