ResNetIncepX: A Fusion of ResNet50 and InceptionV3 for Pneumonia Detection Using Chest X-Rays

Kiran Kumar Kaveti
Assistant Professor
Vignan's Foundation For Science,Technology And Research
Guntur, Andhra Pradesh
kirankumar.institute@gmail.com

Naga Naveen Ambati
Dept of CSE
Vignan's Foundation For Science,Technology And Research
Guntur, Andhra Pradesh
ambatinaganaveen@gmail.com

Swapna Sri Gottipati
Dept of CSE
Vignan's Foundation For Science,Technology And Research
Guntur, Andhra Pradesh
swapnasrigottipati666@gmail.com

Sumanth Vadde
Dept of CSE
Vignan's Foundation For Science,Technology And Research
Guntur, Andhra Pradesh
sumanthchowdary0009@gmail.com

***Abstract*—Pneumonia is an acute and life-threatening lung infection that needs timely and precise identification for proper management. Conventional diagnostic tools are based on expert interpretation of chest X-rays, which can be subjective and time-consuming. DL has transformed medical image analysis by facilitating automated diagnosis. Here, we propose ResIncepX, a hybrid architecture merging ResNet50 and InceptionV3 for the classification of pneumonia. ResNet50 picks up deep spatial features, and InceptionV3 picks up multi-scale patterns, resulting in better accuracy. Our model registers 95.19% accuracy, better than ResNet50 and InceptionV3 separately. Rigorous testing on a database of 5,856 chest X-ray images confirms its better performance. The hybrid method minimizes misclassifications and increases diagnostic reliability. ResIncepX provides an effective, AI-based solution for pneumonia detection, aiding early diagnosis. This innovation aids healthcare professionals in enhancing patient outcomes.**

***Index Terms*—Pneumonia detection, chest X-rays, deep learning, ResNet50, InceptionV3, hybrid model, medical image analysis, Convolutional Neural Networks (CNN), Deep Learning (DL).**

I. Introduction

Pneumonia is a serious respiratory infection that significantly contributes to global morbidity and mortality. It affects over 450 million individuals each year and accounts for more than 4 million deaths, representing nearly 7% of total global fatalities. Young children, particularly those under five years old, are at high risk, with pneumonia responsible for approximately 808,920 deaths in 2017—more than the combined fatalities from cancer and HIV. If preventive measures are not strengthened, projections indicate that over 11 million children under five may lose their lives to pneumonia by 2030.

The COVID-19 pandemic, which emerged in 2019, further intensified pneumonia-related health challenges. In its first year, the virus led to over 63.2 million infections and approximately 1.47 million deaths. Severe cases of COVID-19 often resulted in pneumonia, making it difficult for healthcare providers to distinguish between viral pneumonia, bacterial pneumonia, and COVID-19 pneumonia using conventional imaging techniques. Although CXR is widely used due to its affordability and accessibility, accurate interpretation remains difficult, especially in regions with limited access to trained radiologists. Errors in diagnosis can delay treatment, leading to poor patient outcomes.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized pneumonia detection in medical imaging. Several CNN architectures, including CNN (87.78%), InceptionResNetV2 (88.94%), Xception (90.7%), VGG16 (91.66%), ResNet50 (93.43%), and EfficientNetV2L (94.02%), have demonstrated strong performance in classifying pneumonia cases. However, real-world implementation is still hindered by challenges such as dataset variability, overfitting, computational complexity, and the need for improved generalization.

In response to these constraints, this study introduces ResIncepX, a hybrid deep learning model incorporating ResNet50 Using InceptionV3 to identify pneumonia from X-ray pictures of the chest. ResNet50 is used to extract deep spatial features with a correctness of 93.43%, while InceptionV3 is used to capture multi-scale image patterns with a correctness of 92.76%. Through the blending of these two models, ResIncepX improves feature extraction, reduces false positives and false negatives, and enhances classification correctness, with a general performance of 95.19%.

The suggested model has been extensively validated using publicly available datasets and has proven to be more accurate than individual models and state-of-the-art deep learning approaches. ResIncepX provides a robust and efficient AIdriven method for pneumonia diagnosis, assisting healthcare professionals in early detection and decision-making. Future work will involve enhancing dataset diversity, optimizing the model for real-time clinical use, and incorporating it into computer-aided diagnostic systems to facilitate enhanced medical imaging analysis on a larger scale.

II. Literature Survey

This section reviews recent advancements in pneumonia detection using deep learning techniques from credible journals and conferences.

K Liharika et al. [1] introduced a pneumonia detection model based on DenseNet, EfficientNet, and a hybrid Inception-ResNet. Both DenseNet and EfficientNet resulted in 91% accuracy, whereas the hybrid one boosted the performance to between 92% and 95%.

Eva Rianti et al. [2] worked on the application of transfer learning in detecting pneumonia. Transfer models like Xception, VGG16, and ResNet50 were used for the classification of chest X-rays. The authors documented classification accuracy levels of 82% using Xception, 87% using VGG16, and 94.06% using ResNet50. These outcomes are indicative of the success of deep transfer learning methods in pneumonia classification.

Subrat Kumar Kabi et al. [3] compared ensemble models for the diagnosis of pneumonia by combining SVM, CatBoost, and Logistic Regression. The ensemble model achieved better than individual models.

Shengnan Hao et al. [4] introduced a deep learning framework using YOLO-based object detection for pneumonia localization in chest X-rays. The study focused on detecting multiple lesions within the lungs to aid early diagnosis. The YOLO-CXR model achieved improved accuracy and sensitivity in identifying pneumonia-infected regions.

Yeongbong Jin et al. [5] compared gender-specific performance in classifying pneumonia using DenseNet121, InceptionV3, ResNet50, and Xception. DenseNet121 had more than 90% accuracy, whereas InceptionV3 performed at 93% on the female dataset. ResNet50 had less accuracy in both female and mixed-gender groups, highlighting the influence of the composition of the dataset.

Mudasir Ali et al. [6] proposed a system for pneumonia detection based on EfficientNetV2L, which recorded the highest classification accuracy of 94.02%. The research highlighted the importance of model architecture in enhancing feature extraction and classification performance.

Nazmus Syed et al. [7] explored model fine-tuning and augmentation techniques to enhance pneumonia detection performance. The study utilized LSTM and customized VGG19 models, achieving over 91% and 92.94% accuracy, respectively.

Amer Kareem et al. [8] proposed a hybrid AI-based pneumonia detection system. Their research highlighted accuracy as a key performance metric, demonstrating that hybrid models improve predictive capabilities compared to standalone classifiers.

Mr. M Rajeev Kumar .[9] explored a pneumonia detection method that uses DL architecture with VGG16 and attention mechanisms, which achieved a high classification accuracy of 93.53%. The study highlighted the effectiveness of transfer learning and feature enhancement techniques in improving diagnostic performance on chest X-ray images. Thenmozhi M. [10] proposed an automated machine learning framework using CNN for using chest X-ray pictures to diagnose pneumonia. Their framework was highly sensitive and specific to bridge the diagnostic gap due to a shortage of radiologists and improve early disease detection for improved patient outcomes.

In general, these studies emphasize the progress in detecting pneumonia. Although CNNs, EfficientNet, hybrid models, and ResIncepX exhibit high accuracy, issues like dataset bias and model interpretability are still topics for future work. The combination of deep learning methods continues to improve pneumonia diagnosis, providing better accuracy and lower computational complexity.

III. PROPOSED METHODOLOGY

A. Overview

Our research seeks to create an effective pneumonia detection system based on chest X-ray images and DL methods. We introduce a hybrid model, ResIncepX, which leverages the advantages of InceptionV3 and ResNet50 to improve feature extraction and classification accuracy. The Kaggle chest radiograph pneumonia dataset was utilized, and the model's generalization was improved by the use of data augmentation techniques. The model was optimized with categorical cross-entropy loss and Adam, and Its performance was assessed using the categorization report, confusion matrix, and accuracy, and ROC-AUC score. The findings show that ResIncepX has high accuracy on training, validation, and test datasets, proving its efficiency in pneumonia classification. Future research will aim to improve real-time clinical usability, increase dataset diversity, and implement the model in computer-aided diagnostic (CAD) systems. Our method offers a strong AI solution to enhance the diagnosis of pneumonia with higher precision and effectiveness in the examination of medical images[Fig. 1].

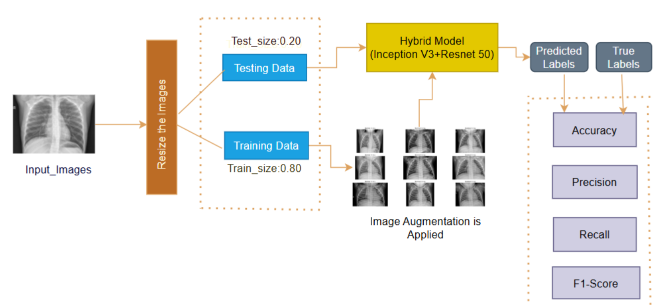

Fig. 1. Pneumonia Detection Model Architecture

B. Dataset Description

The dataset employed in our research is Kaggle's Chest X-ray Pneumonia dataset with 5,863 X-ray images divided into pneumonia and normal classes, as outlined in Table I. It is divided into test, validation, and training sets to facilitate balanced model evaluation. This dataset is vital for the training and evaluation of our ResIncepX model, improving the accuracy of pneumonia detection with deep learning.

TABLE I
DATASET DISTRIBUTION

	Pneumonia	Normal	Total
Test	390	234	624
Train	3875	1341	5216
Validation	8	8	16

C. Deep Learning Models

Deep learning has greatly improved medical image analysis, especially in detecting pneumonia from chest X-rays. Convolutional Neural Networks (CNNs), ResNet-50, and InceptionV3 have proven to be highly accurate and efficient in computer-aided disease diagnosis.

1) CNN: The networks utilize convolutional layers in detecting patterns such as edges and textures, as well as utilizing pooling layers for shrinking the dimensions of the data, thus the process becomes faster. The more complex the feature the network discovers with depth is, the higher the effectiveness rate of CNNs becomes, thus it is so efficient in doing tasks like identifying pneumonia in images. In the last stage, the fully connected layers utilize these features to label images as normal or pneumonia. Through the automatic detection of significant patterns, CNNs enhance diagnostic accuracy and help healthcare professionals identify diseases more accurately.

2) ResNet-50: Residual Network-50 is a 50-layer deep learning architecture used to address issues such as the vanishing gradient problem in extremely deep networks. Skip connections, or residual connections, are applied so that information does not get lost while passing through layers, enabling the network to learn more effectively. ResNet-50 is constructed using convolutional layers, batch normalization, and ReLU activation and is exceptionally efficient at extracting significant features from images. With its deep architecture and capacity to preserve critical details, ResNet-50 enhances accuracy and performance in intricate image recognition tasks. A residual block is formulated as:

$$y = f(x) + x \tag{1}$$

3) InceptionV3: InceptionV3 is a deep convolutional neural network framework that is tailored for image classification tasks. It is a variation of the Inception network, which has been enhanced with factorized convolutions, asymmetric convolutions, and auxiliary classifiers for improved efficiency and accuracy. The model achieves cost reduction by utilizing smaller convolutions rather than huge ones while delivering high performance. InceptionV3 has extensive applications in image classification, object detection, and medical imaging, among others, and provides an equilibrium between efficiency and accuracy. Its optimized design and modular architecture have made it the go-to choice for deep learning applications that need a high level of precision. The Inception module combines different convolutions:

$$Y = \text{concat}(F_1(X), F_3(X), F_5(X), F_{\text{pool}}(X)) \tag{2}$$

4) Hybrid Model: The proposed ResIncepX model integrates ResNet50, Inception V3 architectures to leverage their strengths.

The hybrid model is designed as follows:

1. Feature Extraction: Uses ResNet residual blocks and Inception modules for diverse feature representation.

2. Deep Feature Fusion: Combines multiple convolutional outputs to enhance discrimination power.

3. Final Classification: Uses fully connected layers and softmax for pneumonia prediction.

Mathematically, the model output is given by:

$$Y = \alpha F_{\text{ResNet}}(X) + \beta F_{\text{Inception}}(X) + \gamma F_{\text{Xception}}(X) \tag{3}$$

D. Work Flow

1) **Dataset Collection**: Chest X-ray images are gathered from publicly available datasets such as Kaggle.
2) **Preprocessing**:Data augmentation methods are used to increase model generalization.
3) **Splitting**: Data is split 80% training and 20% testing for model building and validation.
4) **Model Training with Traditional Methods**: CNN, Inception, ResNet V2, Xception, and VGG16 are trained to classify pneumonia cases.
5) **Hybrid Model Implementation**: A combination of **InceptionV3 + ResNet50** is used to improve classification performance.
6) **Model Evaluation**: The trained models are evaluated against the testing dataset based on accuracy and performance measurements.
7) **Accuracy Evaluation**: The top-performing model is chosen based on the results of evaluation.

IV. EVALUATION METRICS

The effectiveness of models for detecting pneumonia employing DL with chest X-rays is evaluated through important evaluation metrics like accuracy, precision, recall, and the F1-score. Accuracy evaluates the total accuracy of the model by including correctly predicted positive and negative cases. Specificity dictates the performance of the model in accurately classifying negative cases with minimal false positives. Precision is the proportion of actual positive cases to all anticipated cases positive cases, and recall (sensitivity) is the model's performance in identifying actual positive cases. The F1-score gives a balanced measure by taking precision and recall into consideration, giving a dependable evaluation for clinical use. These metrics assist clinicians in making knowledge-driven decisions in order to maximize patient outcomes.

V. Results and Discussions

DL model success depends on their capability to accurately analyze and classify data in making predictions. To assess their performance, certain key metrics are employed, including accuracy, precision, recall, and the F1 score. Accuracy describes the overall accuracy of the model at classification, while precision determines the proportion of accurate positive instances out of all the predicted positives. Recall, on the other hand, seeks to minimize false negatives while maximizing true positive cases. The F1 score attempts to balance precision with recall and offers an overall measure of the model's reliability to undertake classification operations. These checks when combined result in a whole analysis of predictive capacity of the model, and the comparison among different models in terms of correctness is depicted by Table II.

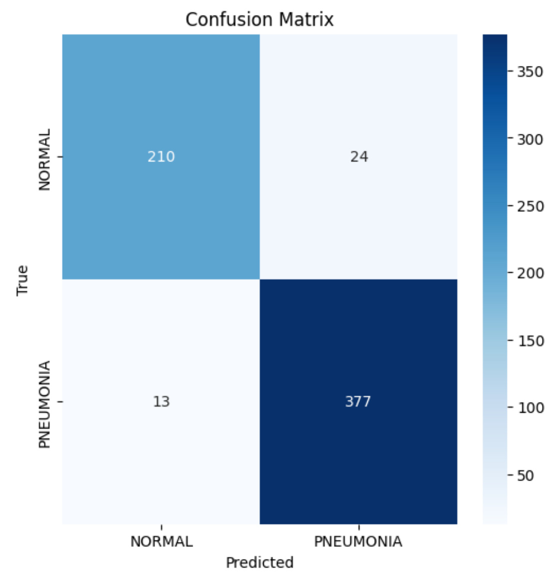

Fig. 2. Confusion Matrix For Hybrid Model

TABLE II
Comparison of Traditional Models and Hybrid Model

Model	Accuracy (%)
EfficientNetV2L	94.02
InceptionResNetV2	88.90
InceptionV3	94.78
ResNet50	92.56
Hybrid Model (InceptionV3 + ResNet50)	**95.19**

The hybrid ResNet50-InceptionV3 model was assessed on the major performance indicators of precision, recall, F1-score, and overall accuracy. The model was found to be highly capable in classifying both pneumonia and normal conditions accurately. For the normal cases, it had an accuracy of 0.94, i.e., 94% of the instances predicted as normal were accurately classified, and a recall of 0.90, i.e., 90% of the actual normal cases were correctly identified, giving an F1-score of 0.92. For the detection of pneumonia, the model had a precision of 0.94 and a remarkable recall of 0.97, giving an F1-score of 0.95. The overall accuracy of 95.19% further emphasizes the effectiveness and reliability of the hybrid model in distinguishing pneumonia from chest X-ray images.

The confusion matrix indicates the hybrid model's performance in classifying chest X-ray images. In all normal instances, 24 had the incorrect label, while 210 had the correct one as pneumonia. Likewise, the model labeled 377 pneumonia correctly, with only 13 being wrongly labeled as normal. The high values densely distributed along the diagonal and the relatively low misclassifications indicate the model's strength at distinguishing pneumonia from normal, further affirming its capability for pneumonia identification tasks, as illustrated in Figure 2.

The ROC curve suggests that the model gets a high real positive rate with fewer false positive rates. With the AUC of 0.98, the model shows excellent classification performance, indicating the strong ability to distinguish between classes in Figure 3.

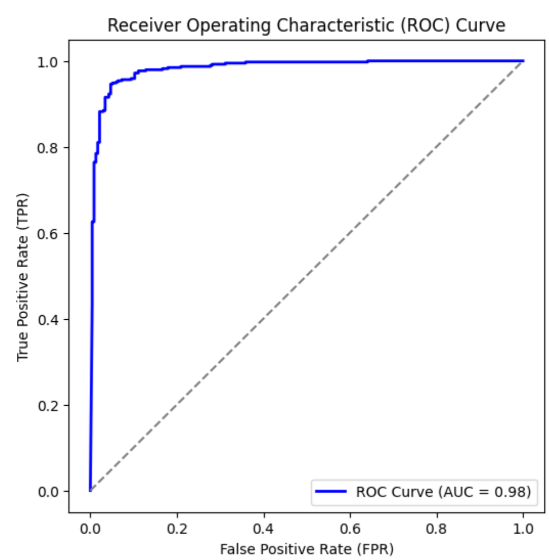

Fig. 3. Receiver Operating Characteristic (ROC) Curve

VI. Conclusion

A graphical tool for evaluating a classification model's performance, the Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR) versus the False Positive Rate (FPR) at different threshold levels. It is used to gauge how discriminant the model is between classes. The solid blue line in Figure 3 represents the classification power of the model, and the diagonal dashed line represents the random guessing. The Area Under the Curve (AUC) 0.98 indicates that the model has high ability to differentiate pneumonia from regular cases. Good classification performance is indicated by values close to 1.0, while values close to 0.5 indicate poor performance. The ROC curve makes selecting an appropriate threshold easier by plotting the trade-off between sensitivity (recollection) and specificity and thus is a critical measure for evaluation in medical diagnosis. The ROC curve also offers information regarding model performance at varying decision thresholds and the determination of the point where the trade-off between the rates of false positives and true positives is best suited for a particular application. ROC curve comparison of several models allows the best-performing model for a particular task to be identified based on its AUC value.

VII. Conclusion

The hybrid architecture that combines ResNet50 and InceptionV3, as proposed, shows great enhancements in pneumonia detection from chest X-rays. The hybrid model effectively utilizes the strengths of the two architectures as complementary to one another, thus allowing it to extract a wide range of features from the input images. Consequently, the model registers an impressive overall accuracy of 95.19%, which outperforms the performance of conventional deep learning architectures commonly applied to medical imaging applications. The accuracy and recall scores further highlight the model's capacity to distinguish between pneumonia and normal cases with high sensitivity, minimizing the chances of misclassification.

The combination of ResNet50's residual learning with InceptionV3's multi-scale feature extraction forms a solid framework that further improves the model's capacity to learn intricate patterns in medical imaging data. This mixed architecture not only enhances accuracy but also helps achieve more robust predictions, which is especially important in medical diagnosis where misdiagnosis comes at a potentially very high price. The evaluation results verify the model's ability to overcome challenges related to chest X-ray examination and therefore promise to be an effective aid to radiologists in clinical environments.

In the future, a variety of upgrades are possible that might continue to increase the performance and use of this hybrid model. As an example, applying data augmentation methods might be able to better generalize the model across more different types of chest X-ray images, hopefully reducing errors and improving robustness. Additionally, in-real-time application of the model in hospital settings might automate the diagnosis procedure, allowing more rapid decision-making and more efficient care for patients. The incorporation of these improvements will not only make the model more usable but also bring it in line with the requirements of healthcare practitioners that depend on timely and precise diagnostic resources.

In summary, this research attests to the incredible potential of deep learning technologies in helping radiologists diagnose pneumonia. With better speed and precision in detecting pneumonia, this combined model can improve patient care as well as the outcome of the treatment. Clinicians' acceptance of such models could result in improved pneumonia cases management, with a final lead to enhanced health care delivery. With technology accelerating, more future developments in the deep learning structures will continue to transform the healthcare sector of medical imaging and diagnosis.

VIII. Future Work

Future improvements to the hybrid ResNet50-InceptionV3 model can focus on enhancing accuracy by integrating attention mechanisms and Vision Transformers (ViTs). Expanding the dataset with a diverse collection of chest X-ray images and incorporating multi-modal data, such as CT scans, can improve the model's generalization and robustness. Deploying the model on cloud-based platforms or edge devices will enable real-time detection, making it more accessible for remote healthcare applications. Additionally, implementing explainability techniques like Grad-CAM will enhance transparency, allowing medical professionals to interpret the model's decisions more effectively.

Further enhancements can include optimizing hyperparameters and leveraging transfer learning techniques to improve adaptability across different datasets. Integrating federated learning will facilitate training on decentralized hospital data while maintaining patient privacy and security.Working with clinicians to refine the model for clinical use and maintaining compliance with healthcare regulations will be critical for deployment in real-world settings. Additionally, extending the model's capabilities to detect other respiratory diseases, such as COVID-19 and Tuberculosis, can further enhance its clinical utility, making it a valuable tool for automated medical diagnosis.

References

[1] S. Hao, X. Li, W. Peng, Z. Fan, Z. Ji, and I. Ganchev, ”YOLO-CXR: A Novel Detection Network for Locating Multiple Small Lesions in Chest X-Ray Images,” *IEEE Access*, vol. 12, pp. 156003–156019, 2024. doi: 10.1109/ACCESS.2024.3482102.

[2] M. Ali *et al.*, ”Pneumonia Detection Using Chest Radiographs with Novel EfficientNetV2L Model,” *IEEE Access*, vol. 12, pp. 34691–34707, 2024. doi: 10.1109/ACCESS.2024.3372588.

[3] S. K. Kabi, R. K. Tripathy, D. Patra, and G. Panda, ”A Novel Approach for the Detection of Tuberculosis and Pneumonia Using Chest X-Ray Images for Smart Healthcare Applications,” *IEEE Sensors Letters*, vol. 7, no. 12, pp. 1–4, Dec. 2023. doi: 10.1109/LSENS.2023.3327580.

[4] Y. Jin, W. Chang, and B. Ko, ”Generating Chest X-Ray Progression of Pneumonia Using Conditional Cycle Generative Adversarial Networks,” *IEEE Access*, vol. 11, pp. 88152–88160, 2023. doi: 10.1109/ACCESS.2023.3305994.

[5] E. Rianti, I. Fitri, and Sumijan, ”Detection of Pediatric Pneumonia Based on Chest X-Ray Image Using Extraction Method,” *2024 12th International Conference on Information*

and Communication Technology (ICoICT), Bandung, Indonesia, 2024. doi: 10.1109/ICoICT61617.2024.10698537.

[6] K. Liharika, K. B. Sri, K. Harish, and C. S. Reddy, ”Detection of Pneumonia in Chest X-Ray Using Deep Learning Enabled Adaptive and Altruistic PSO-based Feature Extraction,” *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kamand, India, 2024. doi: 10.1109/ICCCNT61001.2024.10724021.

[7] S. K. A. S. and Rajashree, ”Deep Learning Based Automated Pneumonia Detection from X-Ray Images,” *2023 7th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, 2023. doi: 10.1109/ICECA58529.2023.10395716.

[8] A. Kareem, H. Liu, and P. Sant, ”Review on Pneumonia Image Detection: A Machine Learning Approach,” *Hum-Cent Intell Syst*, vol. 2, pp. 31–43, 2022. doi: 10.1007/s44230-022-00002-2.

[9] M. R. Kumar and B. G. Vani, ”Implementation of Deep Learning Mechanisms for Detection and Classification of Pneumonia on Chest X-Ray Dataset,” *2024 International Conference on Computational Intelligence for Green and Sustainable Technologies (ICCIGST)*, Vijayawada, India, 2024, pp. 1–6. doi: 10.1109/ICCIGST60741.2024.10717560.

[10] T. MI, N. S. R. S., M. E. K. J., A. R. B., and B. K. L., ”Chest X-Ray Analysis Using Machine Learning for Pneumonia Detection,” *2024 First International Conference on Data, Computation and Communication (ICDCC)*, Sehore, India, 2024, pp. 156–159. doi: 10.1109/ICDCC62744.2024.10961354.