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RESEARCH ARTICLE

Classification of Paediatric Pneumonia Using Modified DenseNet-121 Deep-Learning Model

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ABSTRACT There is a substantial worldwide effect, both in terms of disease and death, that is caused by pediatric pneumonia, which is a disorder that affects children under the age of five. Even while Streptococcus pneumoniae is the most prevalent agent responsible for this sickness, it may also be brought on by other bacteria, viruses, or fungi. An efficient approach utilizing deep-learning methods to forecast pediatric pneumonia reliably using chest X-ray images has been developed. The current study presents an updated version of the DenseNet-121 deep-learning model developed for identifying scans of pediatric pneumonia. The batch normalization, maximum pooling, and dropout layers introduced into the standard model were done so to improve its accuracy. The activations of the preceding layers are scaled and normalized using batch normalization, leading to a mean value of zero and a variance of one. This helps decrease internal variability during training, which speeds up the training process, promotes model stability, and improves the model's overall capacity to generalize. Max pooling is a beneficial technique for reducing the number of model parameters, making the model more computationally effective. Meanwhile, dropout is a preventative measure against overfitting by decreasing the co-dependence of neurons. As a result, the network acquires more durable and adaptive features. Classifying instances of pediatric pneumonia with the help of the proposed model resulted in an exceptional accuracy rate of 97.03%.

INDEX TERMS Batch normalization, chest X-ray, DenseNet, Drouput, Maxpooling, pediatric pneumonia.

I. INTRODUCTION

Pneumonia is a sudden illness that affects the lungs and is one of the primary factors contributing to the death of children all over the globe [1]. Pneumonia is the most deadly illness that causes juvenile fatalities, particularly in low-income and middle-income nations. This is especially true since the condition is often misdiagnosed owing to a lack of resources. According to the World Health Organization (WHO), pneumonia symptoms include rapid breathing, chest indrawing, cough, fever, and difficulty breathing [2]. Other symptoms include a cold and difficulty breathing [3]. Antibiotic treatment may be started early in treating pneumonia if the disease is diagnosed while it is still in its early stages.

Pediatric pneumonia is a significant health problem in low and middle-income countries [4]. It is estimated that

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pneumonia kills more children under the age of five than any other infectious disease, with around 800,000 deaths reported annually. In addition to the high mortality rate, pediatric pneumonia can also lead to long-term health problems such as respiratory impairment and cognitive impairment, which can affect a child's growth and development [5]. The problem is particularly acute in developing countries, where access to healthcare and preventative measures such as vaccination can be limited. Inadequate nutrition, poor living conditions, and exposure to indoor air pollution from cooking fuels such as wood and charcoal can also increase the risk of developing pneumonia [6]. Early recognition and treatment of pediatric pneumonia are essential to reduce the risk of complications and prevent mortality [7]. Prevention measures such as vaccination and improved living conditions can also significantly reduce the incidence of pneumonia in children.

In India, pediatric pneumonia is a severe public health problem since it is a primary cause of sickness and death in children under the age of five [8]. According to the World Health Organization (WHO), in the year 2019, around 127,000 children in this age group lost their lives as a result of pneumonia in India. This figure accounts for 17% of the total number of fatalities worldwide that were caused by pneumonia in this demographic. According to research that was presented at the Lancet Global Health conference in 2020, there would be around 2.3 million cases of pneumonia among children under the age of five in India in 2016. In addition, information obtained from the fourth iteration of the National Family Health Survey (NFHS-4) in 2015–2016 revealed that 3.2% of Indian children under the age of five suffered from pneumonia. The burden of pediatric pneumonia is not evenly distributed across India, and some states and regions have higher rates of pneumonia-related morbidity and mortality than others. For example, a study published in BMC Public Health in 2020 found that the incidence of severe pneumonia was higher in children living in urban slums in Mumbai compared to those living in non-slum urban areas or rural areas.

Radiography [9], often known as chest X-rays [10], is the test most suited for diagnosing pneumonia. Nevertheless, human radiologists still examine medical pictures and are constrained by factors like speed, stress, and experience. It takes several years and a significant financial investment to produce a qualified radiologist. In addition, there needs to be more radiologists working in rural regions of nations with low incomes. Additionally, due to the similarities between pneumonia and other illnesses, diagnosing pneumonia using chest X-rays [11] is a challenging assignment even for well-trained radiologists.

Because of these factors, there is a significant need to create computer-aided diagnostic (CAD) systems that would make it easier to diagnose pneumonia [12]. In the last several years, deep-learning-based computer-aided design techniques have gained appeal in problem resolution for medical issues [13]. In today's world, Artificial Intelligence (AI) methods, such as Deep-learning Convolutional Neural Network (CNN) [14] techniques, have emerged as a helpful tool for separating the many features of lung infections. These methods are now being used throughout the globe. This is because these networks have attained an exceptional level of efficiency for feature extraction by using representation learning and classification [15]. Processing a large number of clinical digital pictures and gaining a knowledge of the spatial information contained within these images, which are prone to varying degrees of noise, has allowed these methods to essentially make significant headway in the development of systems for the identification of disorders. This has been accomplished through the use of computer vision. The drive to improve accuracy resulted in deeper networks, which led to greater complexity costs and an increased number of parameters. However, as these networks became deeper, they moved from having just a few layers, as in AlexNet, to having hundreds of layers, as in ResNet. Deep-learning and multi-agent systems make e-healthcare apps safer and more resilient. The multi-agent system controls agent access to patient data. Each agent has a role and data access rights. Each agent's data is protected by privacy metrics in the system. Deep-learning is added to the multi-agent system to enhance diagnosis and therapy [16].

Major Contribution of the Study: The primary contribution of the suggested study is as follows:

- Pediatric pneumonia has a significant global impact on children under the age of five.
- Streptococcus pneumoniae is the most common cause, but other bacteria, viruses, or fungi can also cause the disease.
- A deep-learning model called DenseNet-121 has been developed to accurately predict pediatric pneumonia using chest X-ray images.
- The model has been improved by adding batch normalization, maximum pooling, and dropout layers.
- Batch normalization helps to reduce internal variability during training and improve model stability.
- Max pooling reduces the number of model parameters, making it more computationally efficient.
- Dropout decreases the co-dependence of neurons and prevents overfitting, resulting in more durable and adaptive features.
- The proposed model achieved an accuracy rate of 97.03% in classifying instances of pediatric pneumonia.

In this study, a deep-learning model for identifying pediatric pneumonia from chest X-ray pictures is presented. The background literature research that was done for this study is presented in Section II. The suggested deep-learning model is shown in Section III. The experimental analysis used to verify the suggested model is presented in Section IV, which is followed by a conclusion and a reference.

II. BACKGROUND WORK

Bodapati and Rohith [17] proposed network that is being offered is an ensemble of many candidate networks, each of which has convolutional and capsule layers that are interleaved. Individual networks are combined with thick layers and then trained as a single model in order to reduce the amount of joint loss that occurs. This proposed method is validated by conducting extensive experiments on the standard pneumonia dataset. Validation of the method is accomplished through the use of the benchmark pneumonia dataset. The comparative analyses show that the proposed model, with an accuracy of 94.84%, generates more general predictions than current methods. The proposed model not only provides scores that are superior to those produced by current models, but it is also incredibly helpful to physicians in the process of diagnosing pneumonia.

Wang et al. [18] suggested a technique that highlights pneumonia information in feature maps by introducing a feature channel attention block called Squeeze and Excitation (SE) to DenseNet. To focus even more on the lesion area, it additionally substitutes max-pooling for average pooling in DenseNet's third transition layer. To avoid neuronal death during model training, the author ultimately chose PReLU after considering several other activation functions. Additionally, the author pre-processed the chest X-ray 2017 dataset by standardizing the results and adding new data. The findings of the experiments indicate that compared to DenseNet, the proposed model's Accuracy is capable of reaching 92.8%.

Rajaraman et al. [19] offered an innovative visualisation method to localise the Region of Interest (ROI) which is regarded as important for model predictions across all of the inputs that belong to an anticipated class. This was done to localise the ROI in question. This tactic was conceived of as a means of narrowing down the region of interest (ROI) that is thought to be significant for model predictions. The modified VGG16 model is capable of achieving an accuracy of 96.2% when it comes to identifying the illness and 93.6% when it comes to differentiating between bacterial and viral pneumonia.

Sadik et al. [20] proposed a modified version of the DenseNet architecture called P-DenseCOVNet for efficient feature extraction and the diagnosis of COVID-19 and pneumonia from segmented lung slices. This innovative design incorporates parallel convolutional routes alongside the traditional DenseNet model to enhance performance by addressing positional arguments. The primary objective of this architecture is to enhance the performance of neural networks, enabling successful feature extraction and diagnosis. Notable achievements were demonstrated with a segmentation test score of 0.97 and an accuracy of 87.5% in identifying COVID-19, common pneumonia, and normal patients. Comparing these results with previous research highlights the exceptional performance of the proposed system, suggesting its potential as a valuable diagnostic tool during the ongoing pandemic, which is anticipated to persist for at least another five years.

Manickam et al. [21] presented a unique technique of deep-learning in this work to automate the diagnosis of pneumonia. The study preprocesses chest X-ray pictures as input to diagnose pneumonia by using pre-trained models from the ImageNet dataset such as ResNet50, InceptionV3, and InceptionResNetV2. The classification of pneumonia as either normal or abnormal (caused by bacteria or viruses) is accomplished by the use of this technique, which is based on the U-Net architecture. In addition to this, it makes use of two different optimization techniques, namely Adam and Stochastic Gradient Descent (SGD), to derive useful features and improve the accuracy of the pre-trained models. The effectiveness of these models is judged based on batch sizes of 16 and 32, respectively. According to the findings, the ResNet50 model that was recommended performed much better than the others, obtaining an accuracy rate of 93.06%, a precision rate of 88.97%, a recall rate of 96.78%, and an F1-score rate of 92.71%.

AlSumairi and Ismail [22] explore the challenge of image-based pneumonia classification and then analyse, build, implement, and evaluate customised convolutional neural networks. In particular, the ResNet-50 and DenseNet-161 models were inherited to construct a tailored deep network architecture and enhance pneumonia classification accuracy. In addition, data augmentation was implemented and integrated with standard datasets to evaluate the models that were proposed. In addition, conventional methods of performance evaluation were used to verify and assess the suggested system. In terms of recall, accuracy, and F1 measurement, ResNet-50 achieved a value of 0.93, 0.94, and 0.94, respectively.

Hashmi et al. [23] developed an enhanced weighted classifier strategy. This approach successfully incorporates weighted predictions from contemporary deep-learning models such as ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3. This strategy is an example of supervised learning, in which the network makes predictions about future events based on the quality of the datasets it was trained on. Transfer learning is a technique that is used to improve the accuracy of deep-learning models throughout the training and validation processes. They employed a pneumonia dataset that was provided by the Guangzhou Women and Children's Medical Center, and they discovered that the recommended weighted classifier model attained the maximum attainable degree of accuracy in testing. As a consequence of this, the model that was built can quickly and reliably identify pneumonia, which assists radiologists in the process of diagnosis.

Aridoss et al [28], suggested deep underwater image classification model (DUICM) employs a convolutional neural network (CNN), a machine learning approach, to perform autonomous classification of underwater images. It is beneficial to train the image and employ classification techniques to effectively categories turbid images based on particular characteristics from the Benchmark Turbid Image Dataset. The suggested system was trained using a variety of underwater photos utilizing CNN models, being capable of handling different types of underwater image generation. Empirical evidence demonstrates that DUICM yields superior classification accuracy compared to turbid underwater imagery. The validity of the developed neural network model is demonstrated by testing it on turbid images with diverse features, hence showcasing its ability to generalize.

III. PROPOSED MODEL

The growing depth of convolutional neural networks led to the issue of information about the input or gradient disappearing as it passed through multiple layers of the network. The authors devised a solution to this problem in the form of a DenseNet structure [24] that makes use of plain connections as a means of addressing it. When calculating gradients in both the forward and backward directions, this method ensures that the information is transferred across layers most effectively and efficiently as possible. Every layer of the network adds new feature mappings to the ones it receives as input from the level above it, and these feature mappings are then distributed to the layers that come after them in the network. Because of this, DenseNet solves the issue of vanishing gradients, improves the propagation of features in both directions, encourages the reuse of features, and cuts down on the number of parameters that are involved.

A. DENSENET ARCHITECTURE

The method of obtaining a predicted label from a conventional convolutional neural network begins with the capture of an input picture. This image is then sent through the network to generate the anticipated label. This forward pass is often quite easy to understand, as seen in Figure 1.

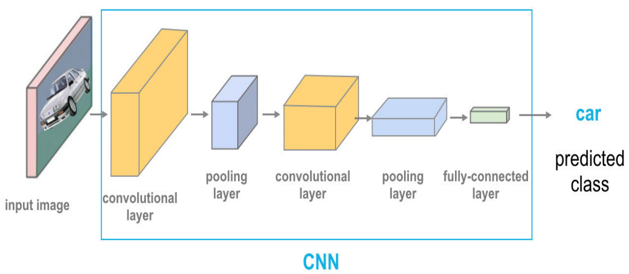


FIGURE 1. Convolutional neural network.

In the design of a DenseNet, each subsequent convolutional layer creates an output feature map by taking the output of the layer that came before it, except the first layer, which is the one that receives the input picture. As the only layer in the network to which the input picture is sent, the first convolutional layer acts as the point of entry from the input layer. Because each layer is directly connected to the one that comes immediately after it, there are a total of L direct connections for the same number of layers because there is a direct connection between every pair of layers that are next to one another. Figure 2 depicts the primary objective of the DenseNet design, which is to depart from the usual CNN architecture.

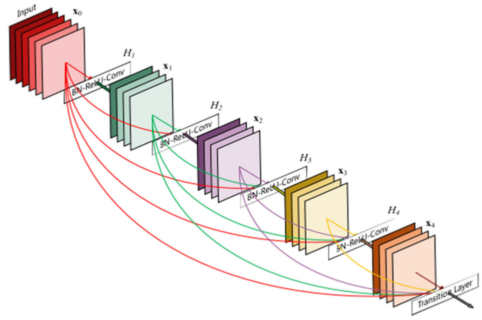


FIGURE 2. DenseNet architecture.

Because each layer of a DenseNet architecture is linked to every other layer in the network, the name "Densely Connected Convolutional Network" was coined. The number of direct connections between L levels is equal to $L(L+1)/2$. The preceding layers' feature maps are used as inputs for the current layer, whilst the current layer's feature maps serve as inputs for subsequent layers.

B. THE PROPOSED DENSENET ARCHITECTURE

In DenseNet, a convolutional network is applied to a single X-ray image X_0. Each of the L layers in the network performs a nonlinear transformation $H_l(\cdot)$, where l indexes the layer. Batch Normalization (BN), rectified linear units (ReLU), pooling, or convolution (Conv) are composite functions of operations that may be used to form $H_l(\cdot)$. The output of the l^{th} layer is designated as X_l.

There are several iterations of the DenseNet architecture in existence, including but not limited to DenseNet-121, DenseNet-160, along with DenseNet-201, amongst others. The numerical value that is included in the names of the models denotes the number of layers that are included inside the neural network. Within the scope of this study, DenseNet-121 is analyzed and improved by adding extra layers to achieve higher levels of precision. The proposed DenseNet architecture for pediatric pneumonia detection is shown in Figure 3.

The following is a list of the layers that are used in the proposed architecture:

- **Zero Padding layer:** It is possible to prevent the loss of information at the edges of a filter by using a technique known as zero-padding. This is useful in situations when the weights of a filter begin to drop down precipitously from their centre.
- **Convolutional layer:** The convolutional layer consists of numerous filters, and those filters are used to produce a feature map by applying them to an input. This map provides a summary of the identified features that are present in the input. An output channel is produced whenever a filter is applied to an input channel and then convolved. This output channel is a matrix of pixels that contains the values that were calculated during the convolutions that took place on the input channel. The

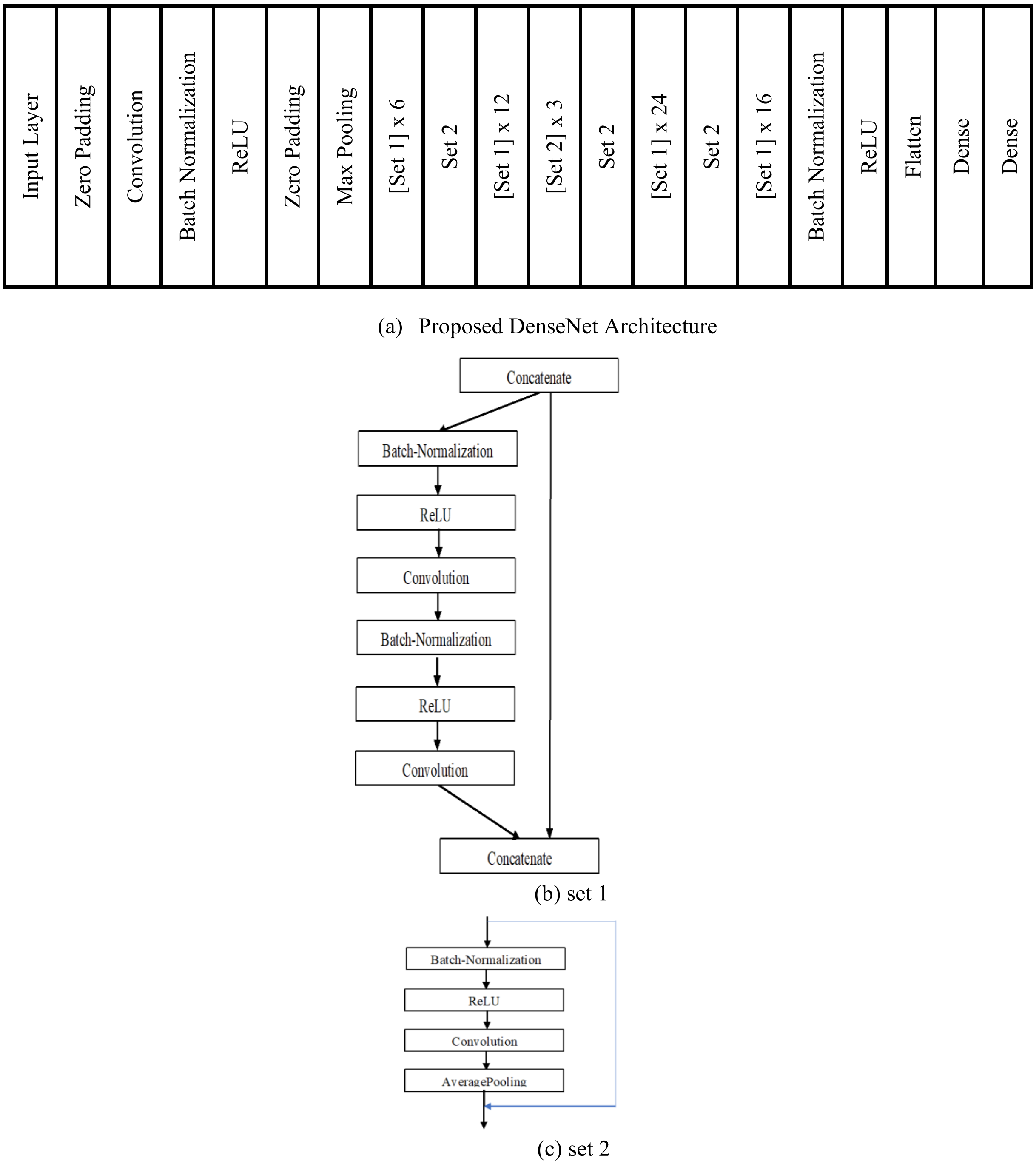


FIGURE 3. Layers in the proposed DensNet architecture.

input channel was the one that was being convolved. When anything like this takes place, the dimensions of our picture are shrunk.

- **Batch Normalization:** During the training of deep neural networks, the "batch normalization" process guarantees that all of the inputs to each layer are consistent throughout all of the mini-batches. As a consequence of this, it helps to maintain consistency throughout the learning process and cuts the amount of time needed for training deep networks by a substantial amount.
- **Rectified Linear Unit (ReLU):** Piecewise linear functions are the ones that are often used to describe the rectified linear activation function, which is more usually known as ReLU. When the input value is positive, it will act by immediately outputting that value; nevertheless, when the input value is negative, it will produce zero. Let's pretend for the time being that an

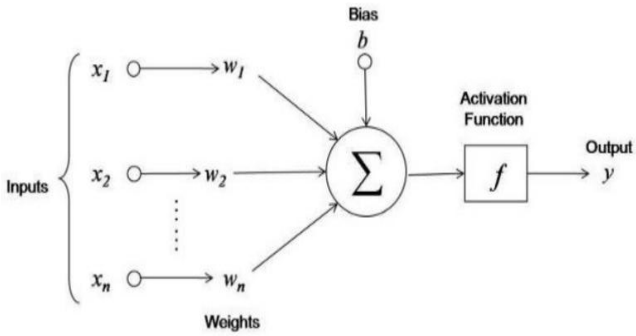


FIGURE 4. Action of the activation function on the bias, weight, and input matrices.

activation function is responsible for influencing the weight matrix, input vectors, and bias terms that are discussed further down.

The activation function of the ReLU may be written as:

$$ReLU(x) = \max(0, x) \tag{1}$$

where 'x' represents the input to the ReLU activation function.

- **Max Pooling:** The max pooling layer is responsible for carrying out a procedure with the same name under the context of the inputs of each layer. This is accomplished by collecting the outputs of the neuron clusters that are contained inside a layer and providing them as input to a single neuron that is located in the layer below it. This pooling technique is an essential part of convolutional neural networks (ConvNets), which stands for "convolutional neural networks." The max pooling approach seeks for and makes use of the neuronal value that is the greatest among all of the neurons in the layer below it. i.e

$$f_{max}(X) = max\{x_i\}_{i=1}^{N} \tag{2}$$

where X: Denotes the input to the function fmax. xi represents the operation of finding the maximum value among a set of values. N represents the total number of values in the set.
- **Flatten:** The function known as "flatten" is responsible for transforming the pooled feature map into a single column, which is then sent to the fully linked layer. The neural network is given an additional layer that is completely linked when dense is applied.
- **Dense:** The name "Dense Layer" was created because it contains critical neurons, and every neuron in this layer is linked to every neuron in the layer below it. This is why the layer is referred to as "Dense." The moniker "Dense Layer" describes this layer well. The output of the convolutional layers is used as a foundation for this layer, which is responsible for performing classification tasks. There is an essential matrix-vector multiplication operation found inside the Dense Layer. This is the point at which the matrix's parameters may be trained and updated via backpropagation. However, backpropagation won't be discussed in this article.

DenseNet uses shortcut connections to skip layers within the network, which allows for more efficient training and better gradient flow. This makes it easier to train deep networks without the problem of vanishing gradients. DenseNet uses fewer parameters than other deep neural networks, which makes it more efficient in terms of memory and computation resources required for training. Shortcut connections in DenseNet encourage feature reuse and decrease the danger of overfitting, which is when a model becomes highly specialized to the training data, restricting its ability to generalize effectively to new data.

The utilization of batch normalization has resulted in a significant acceleration of the training process of the proposed model, as it minimizes the number of iterations necessary to reach convergence. This is because it effectively addresses the vanishing gradient issue that can hamper the learning process. By standardizing the inputs to every layer, batch normalization facilitates the maintenance of the activations within a certain range, which simplifies the optimization of the network weights. It has made the training of deep neural networks more resilient to initialization, reducing the model's reliance on initial weight values. The normalization procedure is effective in decreasing the variance in the inputs to each layer, thus providing greater stability to the network and making it easier to optimize. Additionally, it has led to an improvement in the generalization performance of deep neural networks by reducing overfitting through a decrease in internal covariate shift, enabling network regularization.

Maxpooling minimizes the size of feature maps by choosing the highest value within each pooling region, which leads to a reduction in the total quantity of network parameters as well as the computational cost of the following layers. Maxpooling is an abbreviation for "maximum pooling," which is a method for reducing the size of feature maps. Decreasing the number of parameters also helps prevent overfitting, providing the network with some degree of translational invariance by selecting the maximum activation within each pooling region. As a result, the network becomes less sensitive to small translations of the input image, leading to an enhancement of its generalization performance.

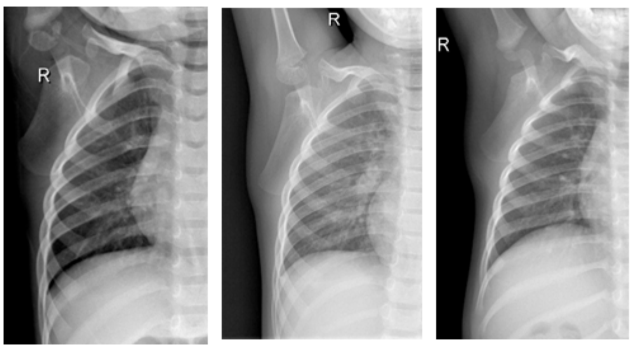
Dropout is a form of regularization that curbs overfitting in neural networks. It achieves this by randomly discarding some units during training, forcing the network to learn more resilient features that are less reliant on specific inputs. This enhanced the network's generalization performance and decreased the probability of overfitting. Furthermore, it minimized co-adaptation between units in the network by compelling each unit to learn useful features independently. This further improved the diversity of the features learned by the network, making it less sensitive to slight input changes

IV. SIMULATION RESULTS

This section presents the results of the tests undertaken to validate the suggested model. When compared to chest X-rays taken of adults, paediatric chest X-rays are more difficult to properly acquire and standardize. This because placing children in a dark room with people watching them through a glass window while operating strange machinery is not an enjoyable experience for them. However, children have a distinct physiology that must be accounted for in X-ray classification algorithms. This is particularly significant given that the vast majority of datasets concentrate only on adult patients.

A. DATASET HANDLING

The data that was utilized in this research came from a paper named "Labeled Optical Coherence Tomography (OCT) and Chest X-ray Images for Classification," which was released in 2018 and uploaded on Kaggle [25]. This publication was the source of the data that was used in this investigation. There are a total of 5,856 X-ray pictures included in this collection. At the Guangzhou Women and Children's Medical Center, these X-ray pictures were obtained from anterior-posterior chest scans of children patients aged one to five years old. There are 1,583 pictures here that depict normal circumstances, whereas the remaining 4,273 demonstrate pneumonia. Figure 5 shows images of the normal class. Figure 6 shows Chest X-ray images of patients with pneumonia.



(a) (b) (c)

FIGURE 5. Chest X-ray of normal-class children.

B. PRE-PROCESSING

The Images that were included in the collection originally came in a variety of dimensions. Because the models for deep-learning anticipate that all of the photos would be the same size, it was necessary to resize all of the images to 180 by 180 pixels. Additionally, the training images underwent a normalization process utilizing their mean and standard deviation to solve the issue of overfitting and streamline the training process. To incorporate modifications into the procedure that was presented, the rotation range was fixed at 20 degrees. On the images that were utilized for validation and testing, we did not do any augmentation; nonetheless, the approaches used for normalization were applied to those images.

C. TRAINING OF PROPOSED DENSENET121 MODEL

The evaluation parameters used in the study include Precision, Sensitivity, Specificity, Area Under Curve (AUC), and Accuracy. These parameters are calculated using the following mathematical equations:

•Precision: Precision is the ratio of true positive predictions to the total number of positive predictions made by the model. It is calculated using the formula:

$$Precision = True\ Positives/(True\ Positives + False\ Positives) \tag{3}$$

•Sensitivity: Sensitivity, also known as recall, is the ratio of true positive predictions to the total number of actual positive instances in the dataset. It is calculated using the formula:

$$Sensitivity = True\ Positives/(True\ Positives + False\ Negatives) \tag{4}$$

•Specificity: Specificity is the ratio of true negative predictions to the total number of actual negative instances in the dataset. It is calculated using the formula:

$$Specificity = True\ Negatives/(True\ Negatives + False\ Positives) \tag{5}$$

•Area Under Curve (AUC): AUC is a measure of the model's ability to distinguish between classes. It represents the area under the receiver operating characteristic (ROC) curve and is calculated using integration or approximation methods.

•Accuracy: Accuracy is the ratio of correct predictions to the total number of predictions made by the model. It is calculated using the formula:

$$Accuracy = (True\ Positives + True\ Negatives)/(True\ Positives + False\ Positives + True\ Negatives + False\ Negatives) \tag{6}$$

These evaluation parameters are essential for assessing the performance and effectiveness of the deep-learning model in classifying pediatric pneumonia using chest X-ray images. The values of the evaluation parameters, which are named Precision, Sensitivity, and Specificity, are shown in Table 1. All of the values for sensitivity and specificity are set to 1 which is the same for both classes. The precision is set to 0.965 for both classes.

TABLE 1. Evaluation parameters.

	Normal	Pneumonia
Precision	0.97	0.96
Sensitivity	0.99	0.98
Specificity	0.99	0.99
Area Under Curve	0.963	0.963

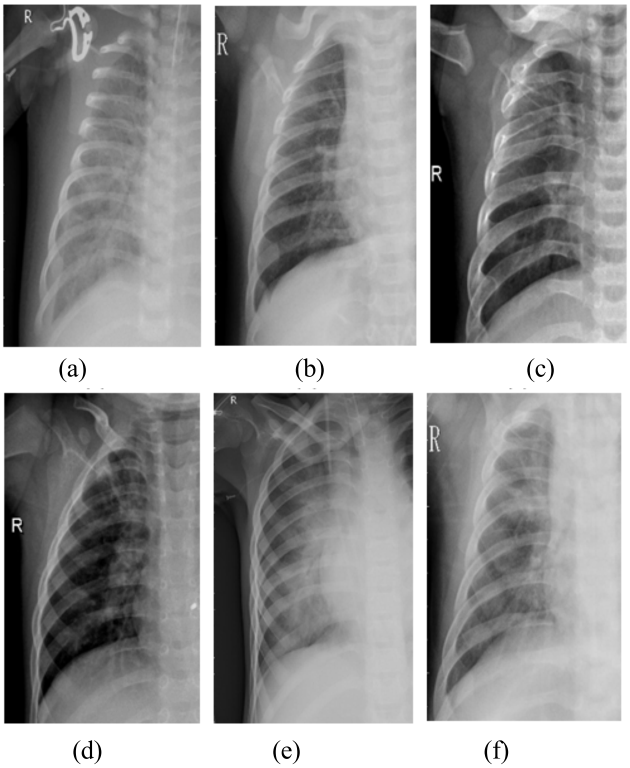


FIGURE 6. Chest X-ray images of children with pneumonia.

When using transfer learning, the model parameters already have solid starting values as a result of earlier training; hence, only minor tweaks are needed align them with the present task. The weights that were used on the pre-trained model will serve as the basis for the continuing work, with tweaks being made as the training progresses. To circumvent the constraints imposed by a lack of resources, we added a new classifier to the highest layer. To be more specific, just the last few layers of the convolutional network were fine-tuned for feature extraction. To evaluate the effectiveness of several well-known pre-trained networks, such as ResNet-50, VGG-16, MobileNetV2, and DenseNet-121, we carried out our evaluations using the appropriate metrics.

ResNet-50: To get better results with image identification, ResNet-50 has been pre-trained using the ImageNet dataset, which included 184 × 184 × 3 chest ×-ray pictures. It had a fully linked layer with 2048 units and another layer with 64 units, and both of these layers included ReLU activation, dropouts, and batch-normalization capabilities.

VGG-16: The top layers of the VGG-16 network, which had also been pre-trained on ImageNet, were omitted from the analysis. To classify the output, a layer that was completely linked and comprised of two thick layers, each of which included 4096 ReLU-triggered units, was applied. After achieving results on the test data, the dataset was fine-tuned such that it could be used again.

MobileNetV2: Using a network that had already been pre-trained on ImageNet, we first conducted feature extraction, and then moved on to global average pooling. After that, the data was inputted into a completely linked layer that used ReLU activation and had a total of 4096 units, with 512 of those units being dedicated to each layer. A Softmax function was used to carry out the classification.

DenseNet-121: After the features were extracted from the ImageNet pre-trained network, global average pooling was performed on the data before it was input into a fully connected layer. This fully connected layer consisted of dense layers with 1024 and 512 units, both of which used ReLU activation. Following that, categorization was carried out with the use of a Softmax function.

TABLE 2. A comparison of the proposed model's metrics with those of other individual networks.

Model	Sensitivity	Specificity	Precision	AUC	Accuracy	Training Time (secs)
ResNet-50	1	1	0.83	93.27	82.20	1123
VGG-16	0.9	0.9	0.94	92.6	94.22	1237
MobileNetV2	0.98	0.98	0.96	98.88	96.36	1336
Proposed DenseNet-121	0.99	0.99	0.97	96.34	97.03	989

According to the results that are shown in Table 2, the model that is proposed performs better than any other models when compared to a variety of assessment criteria. In addition, the recommended network receives a score of 96.34 for its area under the curve and 97.03 for its accuracy.

Table 3 provides a comparison of the many research that have come before. Accuracy, area under the curve (AUC), and precision are all shown to be 97.03%, 96.34%, and 87.70%, respectively, for the model that was assessed and suggested. The substantial research that has been done in this sector has shown some positive results, which have paved the way for the practical implementations of these models to decrease the load placed on healthcare workers and to offset the effects of human error.

Figure 9 demonstrates that the suggested DenseNet-121 requires 989 seconds to finish the training phase, while the existing methods [18], [19], [20], [21], [26], [27] take 1012, 1079, 1135, 1232, 1346, and 1354 seconds accordingly to complete the training phase.

V. DISCUSSION

- The evaluation parameters Precision, Sensitivity, and Specificity are essential for assessing the performance and

TABLE 3. A comparison of the proposed model with baseline models.

Model from Literature	Sensitivity	Precision	AUC	Accuracy	Training Time (Secs)
K.Wang et al. [18]	97.76	92.6	95.21	92.8	1012
Sivaramakrishnan Rajaraman et al. [19]	-	97.7	99.3	96.2	1079
Farhan Sadik et al. [20]	32.4	-	-	65.7	1135
Adhiyaman Manickam et al. [21]	-	88.97	-	93.06	1232
Chouhan et al. [26]	99.62	93.28	99.34	96.39	1346
Enes Ayan et al. [27]	89.1	91.3	87	84.5	1354
Proposed DenseNet-121	99	87.70	96.34	97.03	989

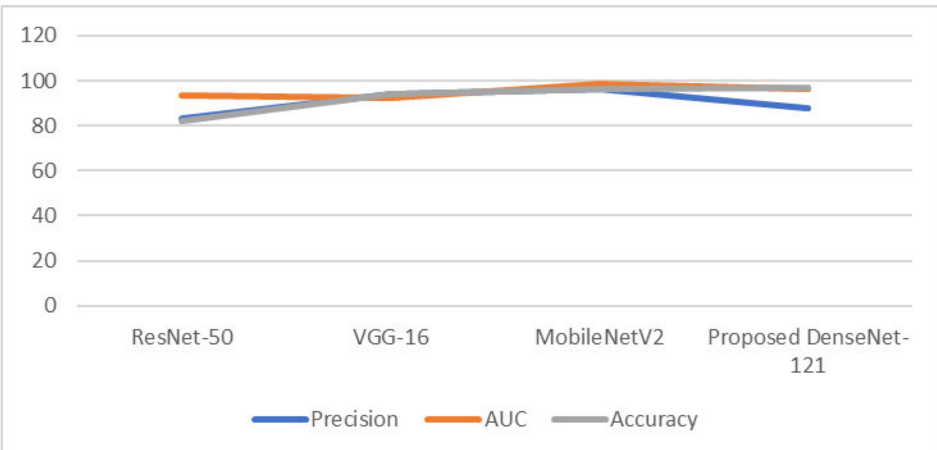


FIGURE 7. Evaluation metrics comparison.

effectiveness of the deep-learning model in classifying pediatric pneumonia using chest X-ray images.

- The values of the evaluation parameters are shown in Table 1, with Precision set to 0.965 for both classes and Sensitivity and Specificity set to 1 for both classes.

- Transfer learning is used in the model, where pre-trained model parameters serve as a starting point and are fine-tuned for the present task.

- Several well-known pre-trained networks, including ResNet-50, VGG-16, MobileNetV2, and DenseNet-121, are evaluated for their effectiveness in classifying pediatric pneumonia.

- Each pre-trained network has specific architecture and features, such as fully connected layers, ReLU activation, dropouts, and batch-normalization capabilities.

- The proposed model, DenseNet-121, performs better than other individual networks in terms of Sensitivity, Specificity, Precision, AUC, and Accuracy, according to the results shown in Table 2.

- The proposed model also outperforms baseline models from literature in terms of Sensitivity, Precision, AUC, and Accuracy, as shown in Table 3.

Limitations of the Proposed System: The following are some flaws that may be recognised:

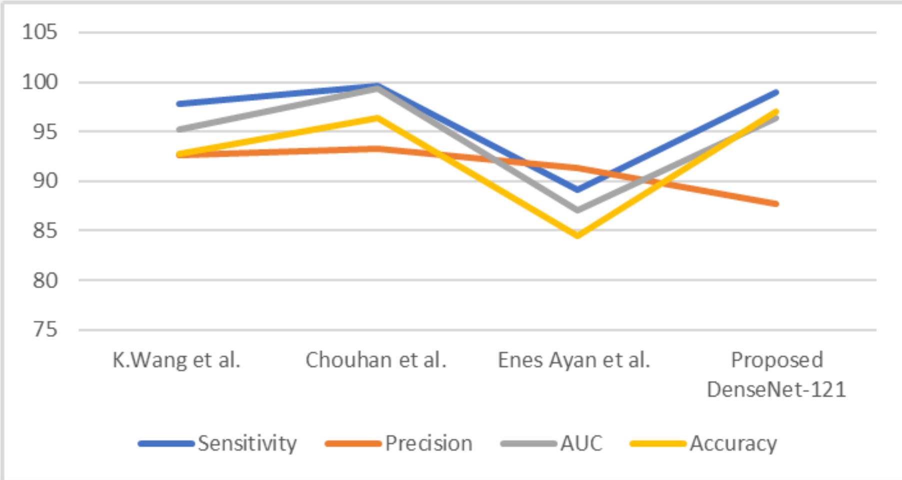


FIGURE 8. Proposed model with baseline models comparison graph.

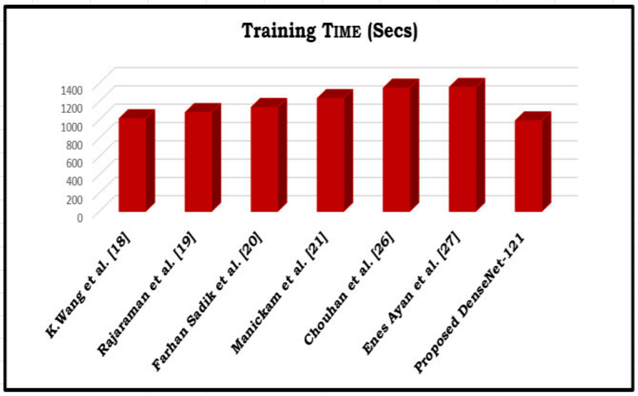


FIGURE 9. The training time analysis with the existing classifier models.

1. Limited Generalizability: The suggested model's capacity to apply to a broader population may be restricted because it relies on a single dataset or a narrow range of paediatric pneumonia cases. Insufficient diversity or representation of demographics, geographic areas, or pneumonia causes in the dataset used for training and testing may undermine the model's efficacy in real-world situations.

2. Data imbalance refers to datasets where one class, such as pneumonia-positive cases, greatly outnumbers the other class. This imbalance might result in a biased performance of the model. If the dataset utilised for training the model exhibits an imbalance, it may encounter difficulties in effectively categorising minority classes, leading to inferior performance, especially in real-world situations where class distributions may vary.

3. Model Interpretability: DenseNet-121, a type of deep learning model, is commonly regarded as a black-box model due to its lack of comprehensibility This means that it is difficult to comprehend the reasoning behind its predictions. The absence of interpretability can provide a notable constraint, particularly in medical contexts where the ability to provide explanations is essential for establishing confidence among healthcare professionals and stakeholders.

4. Restricted Transferability: Although DenseNet-121 is a widely recognised framework, alterations made to it for particular tasks such as paediatric pneumonia classification may not easily apply to other comparable tasks or datasets. The effectiveness of the modified DenseNet-121 model may be constrained to the particular context it was trained, hence limiting its wider application.

5. The deep-learning algorithm's effectiveness is highly reliant on the quality and uniformity of the input photos. The model's accuracy in classifying pneumonia cases can be influenced by factors such as picture resolution, noise, artefacts, and changes in imaging procedures. The model's ability to perform may be negatively affected in real-world scenarios where image quality can vary.

6. Overfitting: Deep learning algorithms, particularly when confronted with intricate structures and restricted datasets, are prone to overfitting, a situation in which the model memorizes training instances rather than acquiring generalizable patterns. If the suggested model is affected by overfitting, its ability to perform on new data may be considerably worse than its performance during training

VI. CONCLUSION

Timely diagnosis and treatment of pediatric pneumonia are important to mitigate potential complications and mortalities. The primary means of avoiding this sickness is by immunization and adherence to hygienic practices. Continued research and innovation are necessary to improve the diagnosis, treatment, and prevention of pediatric pneumonia and to reduce its impact on children worldwide. In this study, several key modifications were introduced to enhance the conventional model. These modifications included the incorporation of batch normalization, max pooling, and dropout layers, with the primary goal of increasing the model's overall accuracy. The enhancement of the model was significantly influenced by the integration of batch normalization, a technique that effectively standardizes the activations of the previous layer by altering and scaling the data to get an average value of zero and a standard deviation of one. Moreover, the improvement of the model was greatly amplified by the integration of max pooling. This was achieved through the reduction of the number of parameters within the model, thus enhancing computational efficiency and bolstering the model's resilience against minor input variations. The inclusion of dropout layers played a vital role in addressing the problem of overfitting. This was accomplished by using a technique to reduce the interdependence among neurons, forcing the neural network to develop more robust and generalizable features. As a result of these enhancements, the proposed model achieved an impressive classification accuracy of 97.03%.

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