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# Pneumonia detection from pediatric lung X-ray images using artificial neural networks

# *Yapay sinir ağları kullanılarak pediatrik akciğer röntgen görüntülerinden pnömoni tespiti*

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# Pneumonia Detection from Pediatric Lung X-Ray Images Using Artificial Neural Networks

### *Highlights*

- *Pediatric Chest X-ray imaging*
- *Data attribute extraction*
- *Classification*

### *Graphical Abstract*

*Pediatric pneumonia X-ray images are retrieved from an index and preprocessed and embedded. Deep learning models are used to compute the feature vector. Feature selection is done to reduce these vectors to a controllable size for processing and analysis. Various machine learning algorithms have been used to classify the images.*


**Figure 1.** A general block diagram of a classification system for X-ray chest X-ray images

*A block diagram of a system for semi- or fully automatic identification of the region to be diagnosed in medical images of pneumonia patients is shown Figure 1. The images were image embedded using deep learning methods. Before applying the large amount of data obtained to different types of machine learning algorithms, data reduction methods were applied. XGBoost (eXtreme gradient boosting), an innovative machine learning algorithm based on decision tree and using gradient boosting in its computations, provided a successful performance.*

***Aim***

*Various machine learning algorithms have been used to classify pediatric pneumonia X-ray images.*

***Design & Methodology***

*Decision Tree (DT), Random Forests (RF), Neural networks (NNs), Logistic Regression (LR), Naive Bayes (NB), The Generalized Linear Model (GLM) and XGBoost classification methods are used.*

***Originality***

*5856 X-Ray images were used in this study. 4273 images were categorized as Pneumonia and 1583 as Normal.*

***Findings***

*Accuracy, precision, sensitivity and F-Score values were found to be close to each other. XGBoost gave much better results in terms of performance compared to other classification methods.*

***Conclusion***

*While the Sensitivity, Specificity, Precision, Negative Predictive Value, False Positive Rate, False Discovery Rate, False Negative Rate, Accuracy, F1 Score and Matthews Correlation Coefficient of the methods used were close to each other, XGBoost gave slightly better results than other classification methods.*

***Declaration of Ethical Standards***

*The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.*

# Pneumonia Detection from Pediatric Lung X-Ray Images Using Artificial Neural Networks

***Araştırma Makalesi / Research Article***

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**ABSTRACT**

Studies on medical imaging have increased significantly in recent years. Thanks to semi- or fully automatic region recognition in medical imaging, doctors have a very important facility for diagnosis. Especially in countries where such medical specialists are scarce, it is very important to support treatment without a specialist doctor. The small air sacs known as alveoli are the most affected by pneumonia, an inflammation of the lungs. Early detection and accurate diagnosis is an important component of providing the right treatment conditions to cure patients and reduce harm while eliminating inflammation. In this study, chest X-ray images of paediatric patients with pneumonia and healthy individuals were studied. A pre-trained SqueezeNet deep learning model was used to compute the feature vector of paediatric pneumonia chest X-ray (CXRs) images. The obtained large data was reduced to a controllable size with PCA and statistical feature selection algorithms. Within the scope of the study, 7 different machine learning models available in the literature were used for Pneumonia detection. XGBoost (eXtreme gradient boosting) is an innovative machine learning algorithm based on decision tree and using gradient boosting in its calculations. It achieved 97.01% success with high classification performance. It is thought that the XGBoost method will help radiologists diagnose the disease more accurately and faster.

**Keywords: Medical imaging, Machine learning, Pediatric Chest X-ray.**

# Yapay Sinir Ağları Kullanılarak Pediatrik Akciğer Röntgen Görüntülerinden Pnömoni Tespiti

**ÖZ**

Tıbbi görüntüleme konusundaki çalışmalar son yıllarda önemli ölçüde artmıştır. Tıbbi görüntülemede yarı veya tam otomatik bölge tanıma sayesinde doktorlar teşhis için çok önemli bir kolaylığa sahiptir. Özellikle bu tür tıp uzmanlarının az olduğu ülkelerde, uzman bir doktor olmadan tedaviyi desteklemek çok önemlidir. Alveol olarak bilinen küçük hava kesecikleri, bir akciğer iltihabı olan pnömoniden en çok etkilenenlerdir. Hastaları iyileştirmek ve iltihabı ortadan kaldırırken zararı azaltmak için doğru tedavi koşullarını sağlamanın önemli bir bileşeni erken teşhis ve kesin tanıdır. Bu çalışmada, pnömonili pediatrik hastaların ve sağlıklı bireylerin göğüs röntgeni görüntüleri üzerinde çalışılmıştır. Pediatrik pnömoni göğüs X-ray (CXRs) görüntülerine ait özellik vektörünü hesaplamak için önceden eğitilmiş SqueezeNet derin öğrenme modelli kullanılmıştır. Elde edilen büyük boyuttaki veriler PCA ve istatiksel özellik seçimi algoritmaları ile kontrol edilebilir bir boyuta indirilmesi sağlanmıştır. Çalışma kapsamında literatürde mevcut olan 7 farklı makine öğrenmesi modeli Pnömoni tespiti için kullanılmıştır. XGBoost (eXtreme gradient boosting) karar ağacına dayanan ve hesaplamalarında gradient boosting kullanan yenilikçi bir makine öğrenmesi algoritmasıdır. Yüksek sınıflandırma performansı ile %97,01 başarı elde etmiştir. XGBoost yöntemi ile radyologların hastalığı daha doğru ve daha hızlı teşhis etmelerine yardımcı olacağı düşünülmektedir.

**Anahtar Kelimeler: Tıbbi görüntüleme, Makine öğrenimi, Pediatrik Göğüs Röntgeni.**

## 1. INTRODUCTION

Pneumonia is a lung infection that can result in swelling and fluid accumulation in the air sacs, causing symptoms like coughing up blood, having a fever, experiencing chest pain, and having trouble breathing. Inflammatory cells gather in the alveoli, which are tiny air-filled lung sacs, and blood vessel serum fills them, causing the lung to become infected. In many impoverished nations, pneumonia is the main cause of death for children. According to the World Health Organization, pneumonia causes one in three baby birth deaths [1].

According to the World Health Organization (WHO), pneumonia kills up to 2 million children under the age of five each year, making it the top cause of mortality in this age group. The World Health Organization (WHO) reports that developing countries, particularly those in Southeast Asia and Africa, are to blame for virtually all (95%) pediatric pneumonia cases [2].

A pediatric Chest X-ray (CXRs) creates images of a child's chest, including the lungs, heart, ribs, and other structures. It is a diagnostic imaging procedure. It is a typical imaging tool used by medical professionals to assess a variety of pediatric respiratory diseases,

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including pneumonia. Pneumonia's two main causes are bacterial and viral infections. A typical CXRs displays unobstructed lungs without any out of the ordinary opacifications. While viral pneumonia manifests as a more diffuse "interstitial" pattern in both lungs, bacterial pneumonia is often focally focused in the right upper lobe. While an urgent referral for prompt antibiotic treatment is requested, bacterial pneumonia is treated with supportive care similar to that given for viral pneumonia. Therefore, a prompt and precise diagnosis is crucial. Radiographic information is one of the most important factors in making a diagnosis because CXRsare typically done and can assist distinguish between different types of pneumonia. It is not always possible to interpret radiologic pictures quickly, particularly in low-resource areas where childhood pneumonia has the highest fatality rates.

In order to assist the prompt referral of children needing emergency intervention, it is critical in the classification of pediatric chest radiographs in the diagnosis of pneumonia and also in the differentiation of pneumonia [3]. The diagnosis of pneumonia is made more challenging and complicated by conditions such pulmonary edema, bleeding, and lung cancer. Additionally, radiologists' determinations to diagnose pneumonia can differ from one another. In order to assist doctors in diagnosing pneumonia, computer-aided diagnostic methods are urgently needed [4]. Particularly, early detection of pneumonia is essential for the patient's recovery process as well as for containing the patient to prevent the epidemic from spreading [5].

To identify the existence of pneumonia clouds on CXRs, Abhishek Sharma et al. analyzed 40 analog chest CXRs from healthy and patients who had pneumonia. They created local algorithms to segment and extract the lung region from the images, dividing the healthy part of the lung from the cloudy parts that were infected with pneumonia, and they employed herbaceous thresholding to find the clouds that were afflicted with pneumonia. To determine the ratio of the area of the healthy lung region to the entire lung region, they performed lung segmentation using Python and OpenCV [6].

Edge-based segmentation was used by Mohd Nizam et al. to attempt lung segmentation. They first discovered the lung edges using the Euler number method and got an excellent result, which let them better recognize the edges. They isolated the lung region from these images using the Canny filter, and then they estimated the separated lung areas [7].

For the purpose of identifying chest disorders, Preeyanan Pattrapisetwong et al. performed lung segmentation based on shadow filter and local threshold on chest radiographs. They take a three-step technique, starting with pretreatment, estimating the original lung field, and then removing noise. The proposed technique has performance measures that are above 90% (overlap, accuracy, sensitivity, specificity, precision, and F-score) [8].

For the recognition method they created for diagnosing pneumonia, Mesut Togacar et al. employed readily available CXRs pictures. In order to extract features from the generated image set, an evolutionary neural network (ENN), one of the deep learning models, was used. Different classifiers were used to compare the features that were extracted for the disease diagnosis. A high success rate of 95.8% was achieved with the support vector machines (SVM) used in the classification procedure as a consequence of the comparison [9].

(Kumar Acharya & Satapathy, 2020) suggested utilizing a deep neural network to automatically identify pneumonia from a chest radiograph image. By dividing the CXRs picture into two pieces, viral and bacterial pneumonia infections were distinguished. [10].

(Rahman et al., 2020) sought to use digital X-ray pictures to automatically identify viral and bacterial pneumonia. Following a thorough explanation of the improvements made in the precise identification of pneumonia, the authors' technique is described. For transfer training, four different pre-trained ESA models were used. AlexNet, ResNet18, DenseNet201, and SqueezeNet are the models in question. For the transfer learning-based classification task, a total of 5247 CXRs images—including bacterial, viral, and regular CXRs images—were preprocessed and trained. Transfer learning was utilized for classification after data preparation. The results of the trial showed a 98% accuracy [11].

A convolutional neural network (CNN) ensemble method was put forth by Ayan et al. for automatically diagnosing pediatric pneumonia. Using the proper transfer learning, they trained seven well-known CNN models on the ImageNet dataset. The final findings were achieved by integrating the predictions of the CNN models with the ensemble approach during testing. Out of the seven models, one was chosen for the ensemble method. Additionally, they developed a CNN model from scratch and evaluated its performance against that of the ensemble technique. On the test data, the suggested ensemble approach produced impressive results with an AUC of 95.21 and an accuracy of 97.76. Additionally, the suggested ensemble method identified normal, viral pneumonia and bacterial pneumonia in CXRs pictures with a classification accuracy of 90.71. [12].

In a similar method, radiological imaging methods such CXRs images are preferred to diagnose COVID-19 in the early stages. Many studies have used machine learning and artificial intelligence to diagnose diseases in healthcare [13-15].

Pediatric pneumonia X-ray images are retrieved from an index and preprocessed and embedded. Deep learning models are used to compute the feature vector. Feature selection is done to reduce these vectors to a controllable size for processing and analysis. Various machine learning algorithms have been used to classify the images.

It efficiently optimizes memory and hardware resources, especially for gradient boosting algorithms. The

XGBoost algorithm has many advantages, especially focusing on computational speed and the performance of the model, such as regularization, unlike the Gradient Boosting Machines algorithm

AI research in medical imaging is currently focused on the automated detection and categorization of juvenile pneumonia using CXRs images. A trained healthcare practitioner should always make the first diagnosis following a thorough evaluation that includes the clinical history, physical exam, and other diagnostic tests in addition to CXRs pictures. This research aims to detect and classify pneumonia in pediatric CXRs pictures using developments in machine learning and deep learning approaches.

## 2. MATERIAL AND METHOD

In this study, 5856 CXRs pictures were used to identify and categorize pediatric pneumonia. 1583 pictures were labeled as normal, whereas 4273 were classified as pneumonia. 1583 photographs are in the Normal class, whereas 4273 images are in the Pneumonia class. The Guangzhou Women and Children's Medical Center provided the X-ray pictures for this dataset from patients between the ages of one and five. These high resolution, different size CXRs images are available [16].

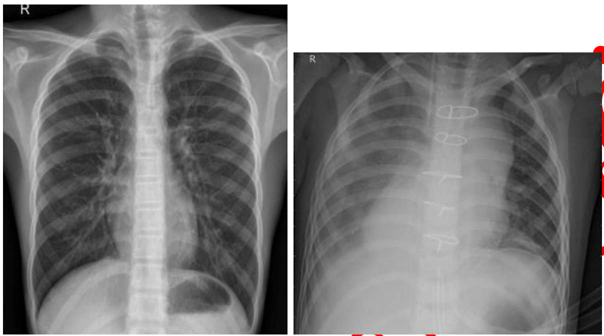

**Figure 1.** CXRs images a) normal b) pneumonia

A radiologist or medical professional with expertise in CXRs will typically conduct an evaluation to determine whether pneumonia is present. Radiologists examine x-ray pictures for certain characteristics that help them diagnose pneumonia. The x-ray pictures that radiologists look at to find pneumonia are displayed in Figure 1. Some characteristics that are considered when identifying pneumonia from CXRs pictures include:

Alveolar morphology The characteristic look of the air sacs (alveoli) in the lungs when they are swollen or inflamed is known as the alveolar pattern. On a CXRs, the alveolar pattern appears as foggy whiteness.

Interstitial pattern: The interstitial pattern is connected to alterations in the lungs' connective tissue and airways. The interstitial pattern appears as web-like or line-like patterns in the lung tissue on a CXRs.

Consolidation when fluid, pus, or inflammation replaces the air sacs in the lungs, consolidation happens. Consolidation appears as whiteness or opacity on a CXRs, making the affected area appear heavier than the lung.

Lung segment changes: Numerous lung segments can be locally affected by pneumonia. A CXRs may show various pictures based on the location of abnormalities in the afflicted region.

In the medical industry, making a diagnosis based on a CXRs takes time in the technologically advanced world we live in. Instead, it is a huge time and money improvement to be able to make a diagnostic using already-built technological tools and software [17]. Deep learning models can produce better results than current techniques when trained on CXRs pictures from pneumonia patients [18]. In this study, CXRs pictures that are freely accessible are taught using machine learning techniques. The features derived from the trained datasets and the outcomes produced by various classifiers are contrasted. With the GLM classifier, the best outcome was attained.

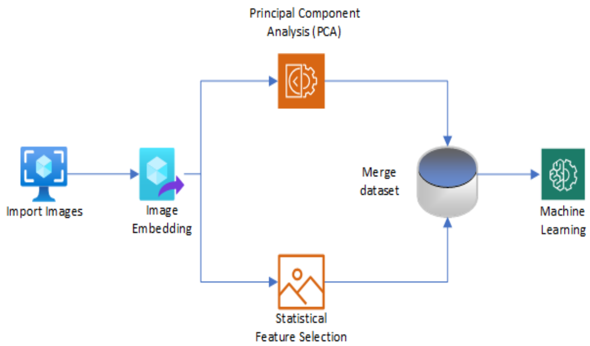


**Figure 2.** Image Embedding and feature extraction

The clustering machine learning method is not directly applied to the images during the classification phase. We must convert them into a more suitable representation, such as number vectors, in order to do the analysis. This procedure is known as embedding. The expression of an image using vectors is known as image embedding, and images with related motifs typically have related vector profiles [19–21].

Figure 2 illustrates the conversion of pediatric pneumonia X-ray pictures from an index into line codes. This method is known as picture embedding. It also includes information like the picture name, image path, image width, image height, and image size in addition to the numerical values of the image's pixels. To calculate the feature vector from the image data, deep learning models are employed. The spreadsheet's columns are labeled during the transfer of these photos.

To learn a low-dimensional feature representation or embedding of high-dimensional images, it entails training a deep neural network with image data. By refining a loss function that enables the network to differentiate between various images while mapping semantically related images to nearby points, an embedding procedure is learned. The learnt embedding can be used as input for a variety of downstream tasks, including image retrieval, classification, and clustering [22], once the network has been trained.

The core of image embedding through transfer learning is used in this work to extract numerical feature vectors from images using pre-trained deep neural embedding. SqueezeNet is a deep image recognition model that uses 50 times less parameters than ImageNet to achieve AlexNet-level accuracy. The ImageNet dataset is used to train the model.

This approach essentially permits the activations of the model representing the images with vectors to be used for image embedding prior to classification. As a result, classification performance is enhanced.

The abundance of features also raises the possibility that the data will demand additional memory space. Finding and subsequently removing an unnecessary subset of attributes during the system's learning phase might improve the system's performance, memory space efficiency, and/or operational cost. Feature selection approaches can be used as a type of dimensionality reduction strategy in this situation because they are crucial for minimizing the amount of features.

## 3. FEATURE SELECTION

One method for bringing the size of the input data under control so that it can be processed and analyzed is feature selection. Finding the most useful feature selection is one of the performance-enhancing elements because it is one of the approaches for reducing the dimensionality of the data. Using feature selection approaches for vast amounts of data attributes, there are numerous studies on dimensionality reduction [23].

The development of an autonomous detection and classification system for juvenile pneumonia utilizing CXRs images starts with the feature selection process. It entails locating and choosing a subset of pertinent features from CXRs pictures that are most useful for differentiating between pneumonia cases and normal cases. In this context, some typical methods of feature selection include:

### 3.1 Manual Feature Selection

CXRs pictures can be manually selected for relevant features using domain knowledge and expert knowledge. For instance, if consolidations, infiltrates, or pleural effusions are present, radiologists may see these visual patterns or features in the images that are suggestive of pneumonia. These visual features can be manually retrieved and added to the classification algorithm's input features.

### 3.2 Feature Selection Based On Machine Learning

From CXRs images, significant features can be automatically selected using machine learning techniques. To find the most crucial characteristics for classification, for instance, Principal Component Analysis (PCA) feature selection techniques can be used. These techniques rank or choose features according to how well they contribute to classification performance by utilizing inherent correlations between features and the target class [24].

A dataset that has been changed using the weights of the principal component or the weights of the numerical data from the images is extracted using principal component analysis (PCA). Large dataset visualizations can be made simpler by PCA.

PCA is a data preprocessing technique that enables m-dimensional data X to be moved to n-dimensional data Y with little loss as a dimensionality reduction approach. Finding the projection vectors that point in the direction of the greatest variation is the major goal of this approach. Unique values in a distinct space are used to represent the projection vectors that are produced. In the same plane, an x vector and a y vector are defined. The equation is used to determine the projection of vector x onto vector y (specified as f).

$$f = \frac{\langle x,y \rangle}{|x|} \cdot y \quad (1)$$

The covariance derived from the data is transformed using the eigenvalue-eigenvector method to produce projection vectors. The eigenvalues are listed in decreasing order of size. The first n eigenvectors of the matrix, which correspond to these ordered d eigenvalues, are used to arrange the matrix's columns. The projection matrix W that offers the best projection is obtained in this manner. The equation is multiplied with the projection matrix and the data to produce the reduced data.

$$Y = W^T \cdot X \quad (2)$$

The particular dataset, the area of the challenge, and the overall pipeline of the autonomous detection and classification system all influence the feature selection methodology that is chosen. To provide accurate and dependable results, it is crucial to carefully assess the performance and generalizability of the chosen features together with the classification method. In order to evaluate the model's performance and resilience prior to implementation in a clinical context, it is crucial to verify and test it using different datasets.

### 3.3. Statistical Feature Selection

Statistical methods can be used to identify the features with the strongest discriminatory power between normal and pneumonia cases. For example, Statistical methods can be selected to evaluate the effectiveness of several visual attributes in distinguishing between two classes statistically.

We have used a number of well-known feature selection and classification algorithms for this investigation. To increase classification efficiency and create the most powerful model, feature selection approaches and several classifier algorithms will be used.

Techniques for feature selection are used in this study, including GINI, gain ratio, information gain, ReliefF, chi-square, and FCBF [25].

*Gini ratio*

A statistical measure of dispersion developed by Corrado Gini, the Gini ratio is also known as the Gini index or Gini coefficient [26]. A population's income distribution is frequently measured using this method because of its simplicity. Depending on the degree between 0 and 1, the measurement value varies.

$$Gini(t_i) = \sum_{i=1}^{N}[p((t_i)^2)] \tag{3}$$

*Information gain*

Another reputable feature selection method that decision tree algorithms employ is information gain (IG) [27]. This method calculates the amount of "information" a feature conveys about the class. In the first stage, a feature with the largest information gain will be put to the test and separated. Following the partitioning of a dataset into attributes, the information gain is based on the decrease in entropy.

$$Entropy(t) = -\sum_t p(j|t)log_2 p(j|t) \tag{4}$$

$$Gain = Entropy(p) - \left(\sum_{i=1}^{k}\frac{n_i}{n}Entropy(i)\right) \tag{5}$$

*Gain to Ratio*

A refined version of information gain called the gain ratio was put forth to overcome the biases and constraints related to information gain [28]. When the sample distribution of entropy is taken into account, the gain ratio is different from information gain.

*Chi-square ( $\chi^2$ )*

To determine if two category variables are independent, statisticians frequently employ the chi-square ($\chi^2$) technique. This approach estimates the variance between anticipated features in data mining [29]. Chi-square can be used to establish from the likelihood (p-value) whether a relationship between two features in a sample (test) truly represents a relationship between these features in the population. In order to compare two features, the algorithm can also decide whether there is a difference between them.

$$\chi^2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{(A_{ij}-E_{ij})^2}{E_{ij}} \tag{6}$$

*FCBF*

Based on the idea of "dominant correlation," a fast correlation-based filter (FCBF) chooses characteristics that are highly correlated with the target variable but have low correlation with other variables if the other feature is more connected with "X" than "X." Once the qualities are more linked with 'X' than with the tested class, the main correlation feature then becomes apparent. A "symmetric uncertainty" (SU) rating coefficient, which is utilized to gauge the degree of feature "conditional uncertainty," and the X divided by Y criteria are used to construct the FCBF's characterization and redundancy analysis concept [30].

$$SU(X,Y) = 2\left[\frac{H(X)-H(X/Y)}{H(X)+H(Y)}\right] \tag{7}$$

*6. ReliefF*

Another feature selection technique that computes weights from data similarly to random data is the ReliefF algorithm, which was created from the Relief algorithm. ReliefF is a feature selection technique that works with several classes of data. In this instance, it is applicable to all data kinds and resilient to incomplete and erroneous data [31].

$$W_i = W_i - (x_i - nearHit_i)^2 + (x_i - nearMiss_i)^2 \tag{8}$$

## 4. MACHINE LEARNING METHODS

We can classify and cluster data using machine learning approaches. They assist in categorizing data after they have a labeled dataset to train on and sort unlabeled data based on similarities across sample inputs [32-34].

Images, drawings, and graphs are examples of complex items with numerical or categorical quantities that can be input into a data set. Similar to inputs, outputs can either be numerical or categorical, and depending on the kind of output variable, models for regression and classification can be used. A classification or pattern recognition model is used when the output is categorical; a regression model is used when the output is numerical, such as age, weight, income level, etc. The primary methods employed in classification and regression models are illustrated in Figure 3

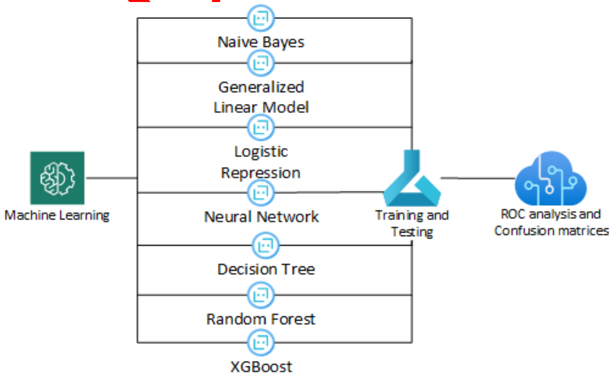


**Figure 3.** Classification and regression models

*1. Decision Tree (DT)*

The DT structure resembles a tree. It is a supervised learning approach used to create classification or regression models. Data classification with DT is a potent technique used in data mining. By repeatedly segmenting a dataset into smaller clusters in accordance with a set of criteria and rules, DT classifies data. Instead of providing only one classifier, ensemble classification approaches produce numerous classifiers. It is an algorithm that categorizes the data in accordance with the conclusions drawn from the predictions made by the classifiers that were developed. The RF algorithm's basic operation is to construct many decision trees, average their values, and then produce results [35]. In a DT the nodes represent where the data is divided and the leaves represent the decisions. The tree structure used is easy to interpret as it can be visualized.

*2 Random Forests (RF)*

The RF algorithm is built using a mix of bagging techniques and decision trees. [36-37]. RF is a machine learning technique for both classification and regression issues. To produce a more precise prediction, the random forest uses many created decision trees. Divide and conquer is the strategy used by the program to boost performance. The best branching variable is chosen by a limited set of variables that are randomly chosen from the entire set of variables in the random subspace approach. RFs are collections of classifiers in the form of trees, where each tree in the forest is reliant on the values of a random vector that has been randomly sampled with the same distribution. It can be viewed as a more sophisticated version of the bagging technique.

*3 Neural networks (NNs)*

There is no reverse orientation in feed-forward NNs; instead, the layers are forward-oriented. Only the cells from the layer before provide food for the cells in the subsequent layer. A feed-forward NN is made up of multiple layers of neurons, which are decision-making nodes. The input layer is on the top, and the output layer is on the bottom. The external environment is connected to the input and output layers. The middle contains at least one hidden layer. Each input neuron in a feed-forward NN is linked to each neuron in the first hidden layer. And each layer's output serves as the input for the following layer [38]. The connections' weights fall between (-1, 1).

*4 Logistic Regression (LR)*

LR is a conventional classification algorithm using linear discriminators that was first put forth by Cox in 1958. The likelihood that the specified input point corresponds to the specified class is the main output. The model constructs a linear border that divides the input space into two sections based on the likelihood ability's value [39]. LR is a straightforward statistical technique. It is one of the most often used classifiers because it performs well on linearly separable classes. A data set containing independent variables is analyzed using LR. Due to its simplicity of usage, LR has recently been used in numerous domains, including biology, economics, and medicine [40].

*5 Naive Bayes (NB)*

The Bayes Theorem is a probabilistic method used by NB. Based on past knowledge of pertinent properties, Bayes' Theorem determines the likelihood that a particular event will occur. The conditional independence assumption of its attributes is another crucial aspect of NB. According to this presumption, one feature's presence has no impact on other features. Using the conditional independence principle, NB classifiers first learn the joint probability distribution of their inputs. Then, using Bayes' Theorem, they generate an output by determining the maximum posterior probability for a given input [41]. The Bayes theorem-based supervised learning technique known as the NB algorithm is used to resolve classification issues. NB calculates variables' probabilities without regard to classes [42].

*6. The Generalized Linear Model (GLM)*

The MLE technique is used to finally convert sequences of instructions into data in the GLM, which is a refinement of traditional linear models. With just a few explanatory variables and non-zero constants, these models enable massively parallel computing at high speeds [43-44].

*7. XGBoost*

Due to its strong predictive potential, quick processing speed, and capacity to manage empty data, XGBoost—which is referred to as an optimized version of the GBM algorithm with numerous adjustments—has many advantages over conventional approaches. It was claimed that the XGboost method performs 10 times quicker than other well-known algorithms for the algorithm originally utilized by Chen and Guestrin in 2016 [45-46]. Because it can do regularization, pruning, working with null values, and system optimization, XGBoost is thought to be superior to other approaches because it is specifically optimized for working with huge data sets [47-48].

To assess the performance of categorization issues, many measures are employed. The metrics derived from the formulas in Table 1 are used to assess classification model performance and provide information on the model's accuracy, precision, specificity, sensitivity, and other performance indicators.

**Table 1.** Performance Metrics dependent on Confusion matrix value

| | |
|---|---|
| Sensitivity | TPR = TP / (TP + FN) |
| Specificity | SPC = TN / (FP + TN) |
| Precision | PPV = TP / (TP + FP) |
| Negative Predictive Value | NPV = TN / (TN + FN) |
| False Positive Rate | FPR = FP / (FP + TN) |
| False Discovery Rate | FDR = FP / (FP + TP) |
| False Negative Rate | FNR = FN / (FN + TP) |
| Accuracy | ACC = (TP + TN) / (P + N) |
| F1 Score | F1 = 2TP / (2TP + FP + FN) |
| Matthews Correlation Coefficient | TP*TN - FP*FN / sqrt((TP+FP)*(TP+FN)*(TN+FP)*(TN+FN)) |

## 5. RESULTS AND DISCUSSION

Prior to training neural networks using X-ray pictures, image embedding was carried out in this study. In order to create a feature vector for each image, deep learning models were employed. With extra columns, a more sophisticated data table was produced.

In order to retrieve pertinent characteristics for data classification, feature selection (FS) is frequently employed to remove irrelevant and distracting information. Data mining's crucial FS and data categorization processes help to locate data attributes in target classes. The high dimensionality of data generated in the medical profession is caused by the presence of redundant, unnecessary, or noisy data. Feature selection and PCA techniques are used to minimize these data. The goal of merging these data is to enhance classification performance. Finding answers to issues unique to machine learning and pattern recognition necessitated feature selection. The classifier's accuracy is increased, and FS keeps it from becoming slowed down by multidimensional complexity. At the same time, it helps to speed up the system in both training and testing phases.

This study employed CXRs pictures to categorize pediatric pneumonia using NB, GLM, LR, DT, NN, RF, and XGBoost machine learning methods.

The dataset in question and the difficulty of the problem influence the algorithm's selection, which has a big impact on computation speed and accuracy. Before choosing the optimal algorithm for the task, it is crucial to carefully enhance the performance of these algorithms and decrease the training time by utilizing appropriate evaluation metrics and validation procedures on the specific dataset of pediatric CXRs pictures.

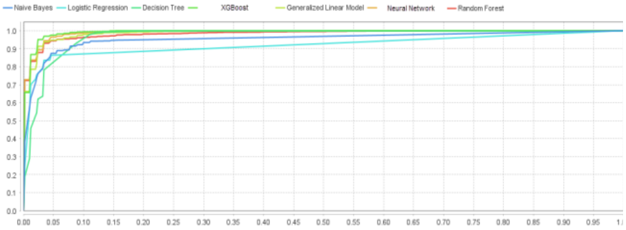


**Figure 2.** ROC Curve

The performance of classification models is frequently assessed using the Receiver Operating Characteristic (ROC) measure. The ROC technique is a practical instrument for assessing the effectiveness of classification models.

**Table 2.** Area under the ROC curve

| DT | NB | GLM | LR | NN | RF | XGBoost |
|---|---|---|---|---|---|---|
| 0.9709 | 0.9547 | 0.9877 | 0.9201 | 0.9709 | 0.9839 | 0.9947 |

The link between a classification model's sensitivity and false positive rate is depicted on a graph called the ROC curve. This makes it possible to evaluate performance at various levels. As a result, you can evaluate the effectiveness of several models or parameter settings and select the optimal model. For classification predictions, ROC values range from 0 to 1.

ROC Curve Generation: In Figure 3, the relationship between the true positive rate (sensitivity) and the false positive rate (false positive rate) is depicted as a graph of the ROC curve. By computing the Area Under the Curve (AUC), it also displays how well the model performs. The AUC value for machine learning classification performance is displayed in Table 2. The model will perform better the closer this value is to 1. The model performs similarly to random guessing if the AUC value is near to 0.5. The machine learning technique called XGBoost had the greatest AUC score of 0.9947.

NB is a probabilistic classifier that relies on the assumption of feature independence. CXRs pictures have been used for feature-based categorization of juvenile pneumonia. Based on characteristics derived from CXRs pictures, Naive Bayes predicted the conditional probability of a particular class (such as normal or pneumonia) with 90.3% accuracy. Table 3 shows the values of classification performances.

The LR method is used in the LR model to analyze independent variables. It employs a sigmoid function to forecast outcomes as a probability value between 0 and 1 in classification problems. Given that it is a linear model, it can process huge datasets quickly.

GLM is a versatile family of statistical models that may be used to a wide range of data sources, including binary classification tasks like the categorization of pediatric pneumonia. Different probability distributions can be used in GLM to simulate the association between features taken from CXRs images and class labels (normal or pneumonia). It has a 95.5% accuracy rate and permits the incorporation of different kinds of predictors.

Numerous hidden layers and neurons make up NN. Between these layers, calculations are carried out utilizing weights and activation functions. To work with massive datasets, more processing power might be required. With additional data, it may also function more effectively.

DT is a nonparametric approach that can be applied to classification applications, such as the categorization of pediatric pneumonia. In order to produce predictions, DT can repeatedly divide the data into various branches and develop decision rules based on attributes collected from CXRs pictures. It can capture non-linear correlations between characteristics and class labels and is simple to understand. It performs classification tasks at a 95.9% efficiency in Table 3.

RF is made up of several different decision trees. Every tree uses random features to determine its classification. It is less prone to overfitting because it is made up of several DT. It can take advantage of parallel processing capabilities and perform well on massive datasets.

Another ensemble method that can be utilized for classification problems, such as the categorization of pediatric pneumonia, is XGBoost. A group of decision trees is assembled by XGBoost, and each new tree is taught to fix the mistakes caused by the ones that came before it. It is renowned for having a 97.01% performance rate in Table 3. Additionally, several machine learning programs make advantage of it. Each year, millions of kids lose their lives to pneumonia, which can be fatal. A sizable number of lives can be saved by an accurate disease diagnosis, prompt treatment, and intervention.

**Table 3.** Values of Classification Performances.

| Measure | DT | NB | GLM | LR | NN | RF | XGBoost |
|---|---|---|---|---|---|---|---|
| **Sensitivity** | 0.8918 | 0.9403 | 0.9024 | 0.9845 | 0.9580 | 0.8725 | 0.9713 |
| **Specificity** | 0.9844 | 0.8886 | 0.9746 | 0.7426 | 0.9459 | 0.9689 | 0.9697 |
| **Precision** | 0.9551 | 0.7576 | 0.9292 | 0.5868 | 0.8677 | 0.9126 | 0.9224 |
| **Negative Predictive Value** | 0.9608 | 0.9757 | 0.9643 | 0.9923 | 0.9838 | 0.9533 | 0.9891 |
| **False Positive Rate** | 0.0156 | 0.1114 | 0.0254 | 0.2574 | 0.0541 | 0.0311 | 0.0303 |
| **False Discovery Rate** | 0.0449 | 0.2424 | 0.0708 | 0.4132 | 0.1323 | 0.0874 | 0.0776 |
| **False Negative Rate** | 0.1082 | 0.0597 | 0.0976 | 0.0155 | 0.0420 | 0.1275 | 0.0287 |
| **Accuracy** | 0.9594 | 0.9026 | 0.9551 | 0.8081 | 0.9492 | 0.9427 | 0.9701 |
| **F1 score** | 0.9224 | 0.8391 | 0.9156 | 0.7354 | 0.9106 | 0.8921 | 0.9462 |
| **Matthews Correlation Coef** | 0.8959 | 0.7796 | 0.8853 | 0.6490 | 0.8773 | 0.8536 | 0.9262 |



This study offers a pneumonia detection method based on deep artificial intelligence. CXRs images and seven common machine learning algorithms were utilized to distinguish between healthy people and people with pneumonia.

The effectiveness of the technique is evaluated using the Kaggle dataset. The performance of the classification was enhanced by the application of feature selection and data reduction. These two data sets underwent parallel training. The overall accuracy of the XGBoost method for the hybrid feature vector was 97.01%. Using larger datasets can enhance the models' overall performance. Future research will focus on enhancing categorization performance. Additionally, it investigates the potential of applying textural image characterization methods to identify pneumonia in CXRs pictures.

Another technique that is frequently used in machine learning algorithms with related models is gradient boosting. The idea underlying boosting is that models are trained in a sequential manner, with each new model aiming to fix the mistakes of the prior one. The decision tree initially matches the data, and a subsequent decision tree can then forecast a new decision tree model using the prior outputs. On the same premise, XGBoost and gradient boosting both operate. In this investigation, XGBoost demonstrated great prediction success. The XGBoost algorithm in particular is designed to function on huge data sets.

The extremely well-liked algorithm XGBoost has uses in the fields of energy, finance, health, and others, and it has a sizable performance and speed advantage over other algorithms. Additionally, XGBoost is 10 times faster than other algorithms and has a great predictive power. A variety of regularizations are also a part of XGBoost, which enhance overall performance and lessen overfitting or overlearning.

By combining the boosting of a number of weak classifiers into one strong classifier, gradient boosting is an ensemble approach. Iterative training is used to develop the strong learner, beginning with a base learner. The same theory underlies XGBoost and gradient boosting. The specifics of implementation are where the primary variations exist. By managing the complexity of the trees, XGBoost is able to improve performance by utilizing various regularization approaches.

The embedders provided in this work by Image Embedding are all trained to do different tasks. Vector representations are generated locally on the user's computer or forwarded to a server for evaluation. Without a network connection, the SqueezeNet embedder provides a quick evaluation on the user's PC. Internet access might be necessary if the user chooses to use embedders other than SqueezeNet. In upcoming research, InceptionV3's image recognition DNN will be trained on the dataset.

The suggested approach can help radiologists diagnose cases effectively because it is suitable for application in real-world situations. We anticipate that our research will help clarify how to diagnose pneumonia. We hope to advance this topic in the future by collaborating with other current datasets on pneumonia. Additionally, we intend to use deep learning algorithms to analyze the data. To address the issue of limited data and enhance generalization, we might also try to use generative models (like GANs) to generate synthetic X-ray pictures.

## DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

## AUTHORS' CONTRIBUTIONS

**Özgür DÜNDAR**: Conducted the analysis and evaluation of the results.

**Sabri KOÇER**: Performed the experiments and the analysis of the results. Also, wrote the manuscript

## CONFLICT OF INTEREST

There is no conflict of interest in this study

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