**Pneumonia Image Classification: A Comparative Study of Naive Bayes and Support Vector Machine Models**

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| **Article Info** |  | **ABSTRACT** |
| ***Article history:***  Received November 14, 2024  Revised January 10, 2025  Accepted January 10, 2025 |  | Pneumonia is a common and fatal disease, which is also one of the leading causes of death worldwide. One of the ways to diagnose this disease is through chest X-ray imaging, and with this, there is a need for an expert radiologist who possesses expertise and experience in the desired domain. According to the World Health Organization (WHO) report, about 2/3 of people in the world still do not have access to a radiologist to diagnose their disease. With this problem in mind, this study proposes a machine-learning classification model that diagnoses pneumonia disease efficiently. The study used a dataset of 290 X-ray images with 145 normal and 145 pneumonia images. The machine learning algorithms used are: Naive Bayes and Support Vector Machine. The performance metrics of each model were done using 10-fold cross-validation. The predictive results show that the Support Vector Machine outperformed Naïve Bayes by attaining an accuracy of 94.83% with precision, recall, and f1-score values of 0.9528, 0.9483, and 0.9480 respectively. NB also demonstrated strong performance with an accuracy of 91.03%.  *This is an open access article under the* [*CC BY-SA*](https://creativecommons.org/licenses/by-sa/4.0/) *license.* |
| ***Keywords:***  Pneumonia  Naïve Bayes  Support Vector Machine (SVM)  Inception-V3  Accuracy  Precision  Recall  F1-Score |

1. **INTRODUCTION**

Pneumonia is one of the leading causes of death worldwide [1], it can affect everyone anywhere, especially children [2]. Pneumonia is a form of acute respiratory infection that is most commonly caused by viruses or bacteria targeting the lungs and it can cause mild to life-threatening illness in people of all ages. When an individual has pneumonia, the alveoli are filled with pus and fluid, which makes breathing painful and limits oxygen intake [3].

Identifying if a person has pneumonia requires general practitioners or doctors specializing in lung conditions [4]. Sadly some countries have not kept pace with the overall economic growth, and their health systems remain weak, which includes doctors who specialize in lung conditions [5]. This lack of general practitioners leads to increased workloads for existing specialists, potential delays in diagnosis and treatment, and overall strain on healthcare systems [6].

This study aims to make a machine-learning model that can classify X-ray images if it has pneumonia. With this tool, it can potentially automate diagnosis which can reduce the time doctors spend on diagnosing pneumonia cases. This allows doctors to focus more on treatment rather than performing or interpreting tests. Additionally, this can also be used as a training and education tool for medical students to learn how to interpret chest X-rays. However, the model is intended solely as a support tool, not a replacement for human judgment.

The rest of this paper is structured thus: Section 2 provides a detailed review of recent literature in the field of pneumonia image classification, Section 3 outlines the methodology employed in this study, and further provides a brief description of the machine learning algorithms used in this investigation. While Section 4 presents the results and discussion, and Section 5 concludes the research.

1. **LITERATURE REVIEW**

Machine learning (ML), once a theoretical concept, has rapidly evolved into a transformative force shaping nearly every aspect of our lives [7]. This technology is also slowly integrated into healthcare, offering innovative solutions for diagnosis, treatment, and operational efficiency [8]. For instance, ML models are being utilized to detect pneumonia from chest X-rays [9]. This section is a summary of existing related papers previously published about detecting pneumonia from chest X-rays that also use Naive Bayes (NB) and Support Vector Machine (SVM).

The researchers in [9] tested the predictive performance of 6 machine learning models. In this review, we focus on Naive Bayes (NB) and Support Vector Machine (SVM). The other models include Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), and AdaBoost (AB). Their dataset consists of 5,856 X-ray images, which include 1,583 normal cases and 4,273 pneumonia cases and is split into 70% for training and 30% for testing. For image embedding they used 5 Deep Convolutional Neural Networks (DCNN) as feature extractors. However, this study will only focus on Inception-V3, the same as the one used in this study. The other DCNNs are AlexNet, SqueezeNet, VGG16, and VGG19. ANN delivered the best overall performance with a 97.19% accuracy, closely followed by LR at 97.08%. Meanwhile, SVM with a linear kernel achieved an accuracy of 85.02%.

Researchers in [10] used five models including, Convolutional Neural Network (CNN), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), and Softmax. In image embedding they extracted the features from the fully connected (FC) layer of a modified CNN architecture using transfer learning. The FC layer generated feature vectors representing each class. The CNN model used in this study was pre-trained on Optical Coherence Tomography (OCT) images before being adapted to the pneumonia detection task. This differs from directly using models like Inception V3. Their dataset is comprised of 5,852 anterior-posterior chest X-ray images, which include 1,581 normal and 4,271 pneumonia cases, and is split into 70% for training, 15% for validation, and 15% for testing. However, in this review, we focus on the SVM, which achieved an accuracy of 99.61%. Among the models, Softmax slightly outperformed SVM with an accuracy of 99.72%.

While Researchers in [11] employed several models, including Multilayer Perceptron (MLP), Random Forest (RF), Sequential Minimal Optimization (SMO), Logistic Regression (LR), and Classification via Regression. The research focused on pixels in lungs segmented Region of Interest (ROI) that are more contributing toward pneumonia detection than the surrounding regions, thus the features of lungs segmented ROI confined area are extracted. It also utilized a total of 412 chest X-ray images containing 206 normal and 206 pneumonic cases from the ChestX-ray14 dataset. And LR model outperform the other models with an accuracy of 95.63% which is the highest among the five.

1. **METHODOLOGY**

This section provides an outline of the research methodology employed in this study.

**3.1. Hardware and Software**

The study was carried out on a system running Windows 10 with a 64-bit operating system. The system uses an Intel Core™ i5-7400 CPU with 16GB Random Access Memory (RAM). The researchers utilized Jupyter and Python version 3.9.15 as the primary programming language for data analysis and model implementation with the following libraries: Math, NumPy, Pandas, PIL, OS, Scikit-Learn, Matplotlib, Seaborn, TensorFlow, and Keras.

**3.2. Data Acquisition**

This research employs a dataset from Kaggle [12], a file with 5856 .jpeg files which are anterior-posterior chest X-ray images. The images are carefully chosen from retrospective pediatric patients with age groups between 1 and 5 years from Guangzhou Women and Children’s Medical Center. The image has 2 normal categories pneumonia and normal which are further divided for testing, training, and evaluation [12]. Because of hardware limitations, this study uses 290 images with 145 normal and 145 pneumonia images.

**3.3. Image Embedding**

The main goal and objectives of the proposed system are to diagnose and make a tool that can identify whether a person has pneumonia through chest X-ray images. This study uses a Deep Convolutional Neural Network (DCNN) which is Inception-V3, for feature extraction of the X-ray images.

Inception models were developed by a researcher [13] for the first time in 2014. The structures of inception models and the conventional CNN model are different because they are inception blocks which means lapping the same input tensor with multiple filters and concatenating their results. In 2015, a researcher [15] proposed a new version of the inception models named Inception-V3, an improved version of the previous versions of inception models which are Inception-V1 and Inception-V2, and possesses 24M parameters. Inception-V3 improves the efficiency and performance of convolutional neural networks by introducing clever factorization techniques. Instead of directly using large convolutions (e.g., n x n), it breaks them into smaller, more manageable operations. For example, a 5 x 5 convolution is replaced by two 3 x 3 convolutions, and an n x n convolution is split into asymmetric 1 x n and n x 1 convolutions, reducing computation. Additionally, 7 x 7 convolutions are replaced with multiple 3 x 3 convolutions. Each inception block processes the input in parallel through multiple convolutional filters of different sizes (1 x 1, 3 x 3, and 5 x 5), as well as 3 x 3 max pooling, capturing features at various scales. These outputs are then concatenated and passed to the next module, allowing the network to learn complex features efficiently.

**3.4. Data Pre-processing**

Data processing is an essential aspect of model development. Data acquired in their raw form contain noise and anomalies, which can affect the performance and training process of the model being schooled [15]. In addition to this when preparing input data for a DCNN, it's essential to adhere to specific requirements regarding input shape, color channels, and preprocessing steps to ensure optimal performance [16]. The researchers employed several techniques to clean the data, which included image pre-processing and data normalization:

Image pre-processing is an essential part of image classification to ensure that input images align with the model's expectations. Inception-V3 requires input images in 299x299 resolution and should also have three color channels (red, green, and blue) [17][18]. And since the datasets used are X-ray images they only have 1 color channel (black and white) and inconsistent high resolution. With this in mind, the images are turned to have three color channels, and it is also resized to have a resolution of 299x299. After this, the image is preprocessed using TensorFlow Keras API preprocess\_input so that the images align with the model's training conditions.

Data normalization is a pre-processing technique primarily intended to manage numerical features and is applied to numerical features before the application of classification algorithms. Normalization is crucial to prevent the effect of certain features from being concealed by others, particularly when the ranges of the features are inconsistent [19]. After feature extraction using Inception-V3, the features are normalized to improve model training [20]. The normalization techniques used are Min-Max Normalization for Naive Bayes (NB), and Z-Score Normalization for the Support Vector Machine (SVM).

**3.5. Machine Learning Algorithms**

This section focuses on the machine learning classification models utilized in this study. After image and data pre-processing, the machine learning workflow progresses to the model training stage, where an algorithm is taught to learn from data and produce predictions. This algorithm is specifically responsible for the classification of whether an X-ray image has pneumonia. To find the best classifier for engagement level prediction, several classifiers, including Naive Bayes (NB) and Support Vector Machine (SVM) were tested through a variety of tests.

**3.5.1. Naïve Bayes**

The Naïve Bayes algorithm has its foundation rooted in the Bayes theorem by Thomas Bayes. One of the strengths of this model is its ability to handle missing values. And Unlike other models, Naïve Bayes conserves processing and training time [21][7]. The term ‘naive’ is used due to this algorithm's uncertain independence. With this, researchers in [22] stated that with this ability it's able to converge quicker when compared to several others.

(1)

Where X is the training set of attributes and Y is the given class [7].

**3.5.2. Support Vector Machine**

Support Vector Machine (SVM) is a binary linear classifier. As a non-probabilistic supervised learning algorithm, it utilizes training data and employs a high-dimensional space to construct a set of hyperplanes for data classification. While only the features of test data are provided, the model is trained on the training data to predict the target values. For effective classification of problem instances, SVM relies on selecting the optimal hyperplane [7].

**3.6 Model Evaluation Metrics:**

Evaluation measures are metrics used to assess the results of an experiment [24]. In the context of classification models, different evaluation metrics are used to measure their output. In this study, the main performance evaluation metric is “Accuracy”. However, additional metrics such as recall, precision, f-measure, and confusion matrices are also used to supplement the evaluation of the model's performance. Each model identifies learner engagement levels when assessed using these metrics. A brief description of these metrics is provided below.

**Accuracy (AC)** is a common evaluation metric for classification models. It's calculated as the ratio of well-predicted samples to the total sample of prediction. For a balanced dataset, accuracy is a reliable measure of the model's performance [22].

(3)

In this equation, a true number that is positive is denoted by TP while a true number that is negative is denoted by TN, however, FN denotes a false number that is negative and FP denotes a false positive number [7].

**Precision (PRE)** is computed by dividing all the true positive samples by the sum of the predicted positive samples and predicted negative samples [7].

(4)

A high precision score indicates strong class predictions, while a low precision score reflects weak class predictions [25].

**Recall (RE)** is the ratio of correctly predicted positive results to all actual positive samples, also known as the detection rate. It's calculated by dividing the true positive samples by the sum of the positive samples [7].

(5)

**F1-score (FS)** is the mean value for recall and precision. It offers an indicator of mistakenly graded results [22]. It is regarded as the best metric for measuring the performance of models on an imbalanced dataset. It ranges from 0 to 1, with higher values indicating better model performance [7].

(6)

1. **RESULTS AND DISCUSSION**

This section provides the outcome of the analysis, achieved through running the models using 10-fold cross-validation, with accuracy as the primary metric for evaluating the performance of the models. Additionally, the performance of the models is further assessed using f1-score, recall, precision, confusion matrices, and misclassified images.

**4.1. Model Performance**

Table 1 shows the results of the two models after evaluating their performance using precision, accuracy, f1-score, and recall. Figure 1 provides a visualization of the results. Figures 2 and 3 illustrate the performance of two machine learning models through a confusion matrix, which are NB and SVM classifying X-ray images into two categories: PNEUMONIA and NORMAL. Figures 4 and 5 are the misclassified X-ray images of each model of NB and SVM respectively.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Models | Accuracy | Precision | Recall | F1-Score |
| SVM | 0.9483 | 0.9528 | 0.9483 | 0.9480 |
| NB | 0.9103 | 0.9186 | 0.9103 | 0.9095 |

**Table 1**. Performance Metrics

In the evaluation of the two machine learning models using a 10-fold cross-validation, in Table 1 it can be observed that the performance of all the models accuracy ranges from 90% to 94%. The result shows that all the models can strongly identify whether X-ray images have pneumonia. And with a thorough analysis of the results, indicates that SVM provided the highest accuracy of 94.83%, with a precision of 0.9528, a recall of 0.9483, and an F1-score of 0.9480. The NB model, while performing well, showed slightly lower accuracy compared to SVM, with an accuracy of 91.03%, a precision of 0.9186, a recall of 0.9103, and an F1-score of 0.9095. These results suggest that SVM handles the dataset very well, using kernel functions like the Radial Basis Function (RBF) shows that SVM is a powerful model for this study. While NB performs relatively well, its performance is lower than the other models. Overall, the findings highlighted the effectiveness of all two models and emphasized their potential for application in automated pneumonia detection.

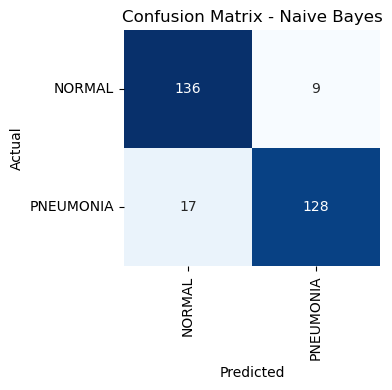
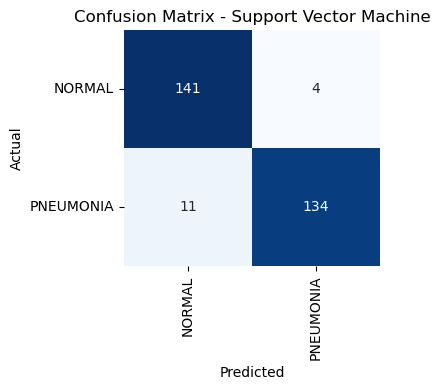
**Figure 1.** Graphical Performance Metrics

Figure 2 presents the performance metrics through a line chart which are: accuracy, precision, recall, and F1-score of SVM and NB.

SVM achieves consistent high across all metrics in both NORMAL and PNEUMONIA classifications, showing the best overall performance among the two models, with performance around 94–95%. The minimal variance between metrics indicates that SVM is a great model in this classification task.

NB shows lower performance than SVM but is still within a decent range for classification tasks, with metrics around 90–92%. Its simplicity and assumptions of feature independence hinder its ability to handle complex interactions in the data. Overall, While NB is effective for simpler patterns, NB is less suitable for handling overlapping or subtle features.

The graph demonstrates that SVM dominates overall across all metrics, SVM outperforms Naive Bayes, making it the better model for this task. This suggests that SVM handles the complex feature extraction from Inception V3 more effectively. While NB shows high precision but low recall, while it avoids false positives relatively well, it sacrifices recall, which makes it miss more pneumonia cases, a critical issue in healthcare tasks.

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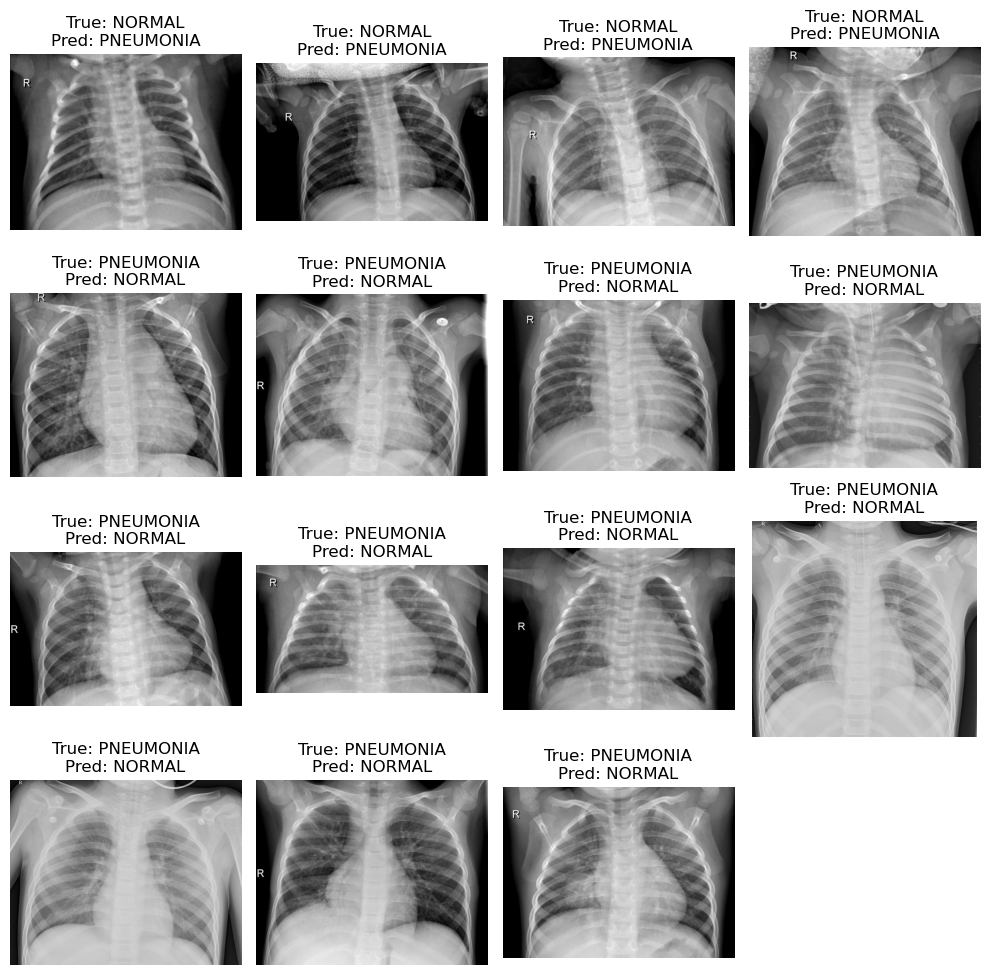
**Figure 2.** SVM Confusion Matrix

**Figure 3.** NB Confusion Matrix

In Figure 2, the confusion matrix for the SVM model shows high accuracy in detecting both NORMAL and PNEUMONIA cases. With only four false negatives, which is critical for pneumonia detection since missing a pneumonia case could have severe consequences. Overall, SVM shows slightly better overall performance compared to Naive Bayes in terms of reducing misclassification.

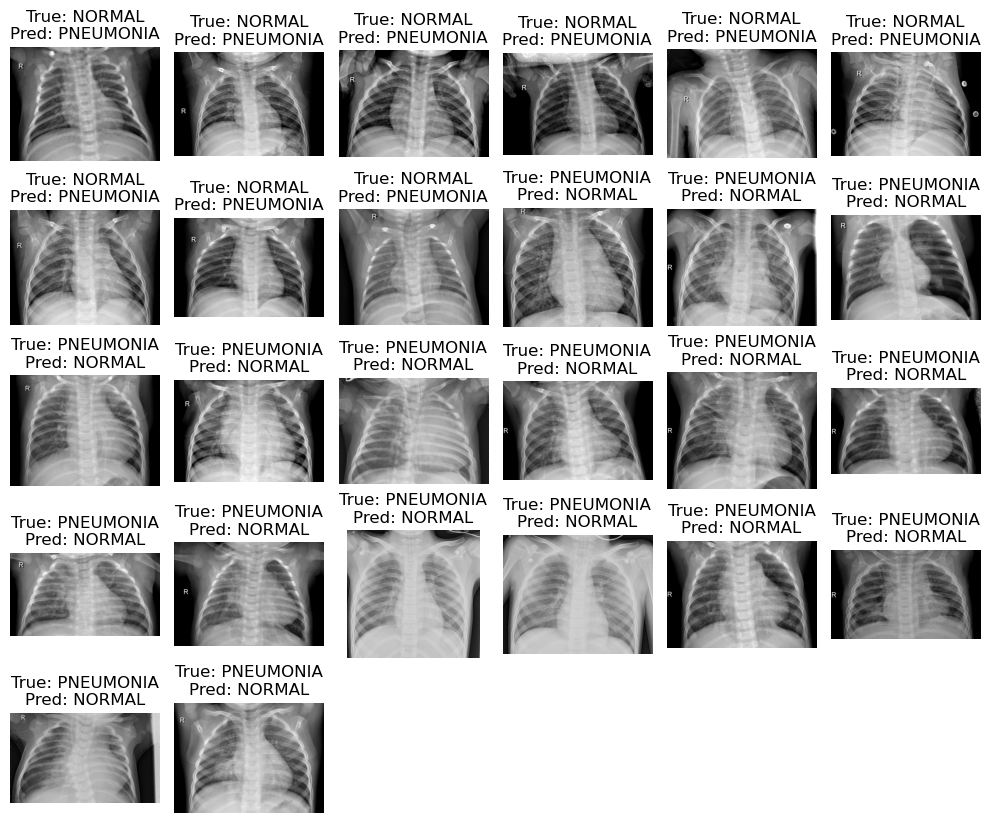
In contrast in Figure 4, NB shows slightly lower accuracy compared to SVM, as evidenced by higher false positives (17) and false negatives (9). Naive Bayes struggles more with classifying pneumonia cases accurately which results in higher false negatives, which is a critical area for improvement. This model may be more prone to noise or incorrect feature distribution assumptions, which could explain the performance gap.

Overall, SVM performs better, particularly with fewer false negatives and positives, making it more reliable for a sensitive task like pneumonia classification. Naive Bayes may not handle complex, non-linear relationships as effectively as SVM, which benefits from Inception V3’s extracted features and its ability to work well with high-dimensional spaces. If the goal is to minimize false negatives which is critical in healthcare, SVM is the better choice. Naive Bayes might be improved with additional preprocessing or feature engineering to better adapt to the data distribution.

**Figure 4.** SVM Misclassified Images

The first row shows chest X-rays where the true label is NORMAL, but the SVM model predicted PNEUMONIA. This suggests slight opacities or irregularities in the lung regions of the misclassified chest X-ray images that resemble pneumonia patterns. The rest of the rows are chest X-rays where the true label is PNEUMONIA, but the model predicted NORMAL. This indicates that the misclassified chest X-rays may lack clear and distinct patterns of pneumonia.

These misclassifications occur in cases where the X-rays are visually less distinct. The model also might be struggling with nuanced or borderline cases where the features extracted by Inception V3 are less pronounced. Overall, the misclassified images suggest that the model performs well for clear cases but struggles with borderline or less distinct cases.

**Figure 5.** NB Misclassified Images

The first and second half rows highlight cases where the model predicted NORMAL as a PNEUMONIA image. The rest of the rows showcase where PNEUMONIA images were predicted as a NORMAL image. It seems that the misclassifications occur for borderline or vague cases which is the same as the SVM model. The NB model might struggle with complex patterns due to its simplicity and assumptions of feature independence, which can lead to limitations in capturing nuanced or overlapping features in X-ray images.

Overall the performance of SVM and NB models suggests that while they handle clear cases effectively, they consistently struggle with less distinct or borderline cases. One of the probable reasons for this is a limitation in the features extracted by Inception V3, the reliance on these features might not fully capture subtle or complex patterns in the X-ray images. This affects NB due to its simplistic assumption of feature independence. In contrast to SVM, which can better model feature interactions demonstrate superior performance.

**4.2. Comparative Discussion**

The researchers in this study have evaluated the performances of the two models namely, Support Vector Machine (SVM) and Naive Bayes (NB) in classifying chest X-ray images if it has pneumonia. The models demonstrate varied strengths and weaknesses, highlighting their effectiveness in this image classification task.

The SVM model demonstrates strong overall performance in the image classification task, achieving consistently high metrics around 94–95%. However, it shows a slight bias toward missing some PNEUMONIA cases, which is evident in the confusion matrix and the misclassified images.

The NB model exhibits lower performance compared to SVM with metrics ranging between 90–94%. The NB model struggles with complex patterns due to its simplicity and assumptions of feature independence. These misclassifications highlight the limitations of using Naive Bayes for a challenging problem like medical imaging.

This study confirms that SVM is the most effective model for classifying chest X-ray images, achieving the best balance between precision and recall. NB, while effective for simpler tasks, falls short in comparison due to its inherent limitations.

1. **CONCLUSION**

Pneumonia is one of the common and fatal diseases in the world, and to treat it, people need access to radiologists. Unfortunately, not everyone has access to these professionals. This study proposes an ML model that can classify chest X-ray images to determine if they indicate pneumonia. Chest X-ray images were used as the dataset to train and test the model. This study also utilizes a Deep Convolutional Neural Network (DCNN), specifically Inception-V3, for feature extraction from the X-ray images. Afterward, the features are pre-processed through data normalization techniques, such as Min-Max Normalization and Z-Score Normalization, and then presented to the classifiers for further processing. Two ML classification algorithms SVM and NB were used to examine the efficiency of the proposed system. Numerous performance evaluation measures, including classification accuracy, precision, recall, and F1-score, were applied. From the experimental results, it is observed that SVM performed exceptionally well, attaining the highest classification accuracy of 94.83%. The findings of this study suggest that SVM is the most effective model for classifying chest X-ray images for pneumonia detection, offering a promising tool for educational and health institutions aiming to classify chest X-ray images for pneumonia detection. Meanwhile, NB provide alternative solutions with varying levels of performance.

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