**Stress Detection Through Image Classification: A Comparative Study of Naive Bayes and Support Vector Machine**

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| **Article Info** |  | **ABSTRACT** |
| ***Article history:***  Received November 14, 2024  Revised January 20, 2025  Accepted January 20, 2025 |  | Stress has emerged as a significant global health concern, affecting individuals across all demographics. Traditional stress detection methods, such as self-reported surveys and biometric sensors, often face challenges related to intrusiveness, cost, and efficiency. This study explores an alternative approach by leveraging image classification techniques to detect stress through facial expressions. The study used a dataset of 280 facial images with 84 Non-Stressed and 196 Stress images. The machine learning algorithms used are: Naive Bayes and Support Vector Machine. The performance metrics of the two models were done using 10-fold cross-validation. The predictive results show that the Support Vector Machine outperformed Naive Bayes by attaining an accuracy of 82.86% with precision, recall, and f1-score values of 0.8312, 0.8286, and 0.81 respectively. NB also demonstrated lower performance with an accuracy of 74.29%.  *This is an open access article under the* [*CC BY-SA*](https://creativecommons.org/licenses/by-sa/4.0/) *license.* |
| ***Keywords:***  Stress  Naïve Bayes  Support Vector Machine (SVM)  Inception-V3  Accuracy  Precision  Recall  F1-Score |

1. **INTRODUCTION**

Stress has become a pervasive issue affecting individuals across various ages and professions. As of August 2024, 31% of adults surveyed worldwide believed that stress was the biggest health problem in their country, indicating a growing recognition of stress as a major health concern [1]. It is also reported that 51% of adults who felt stressed also reported feeling depressed, and 61% reported feeling anxious [2]. It indicates that higher levels of perceived stress are significantly associated with greater variability in negative emotional states, highlighting the complex relationship between stress and emotions [3]. Not only is stress related to the person's emotions, but it also negatively affects the person's body. Chronic stress can lead to high blood pressure, increasing the risk of heart attack and stroke, this shows that stress is also a significant risk factor for various cardiovascular conditions [4][5].

This study aims to make a machine-learning model that uses facial images as inputs to classify a person's emotional state whether the person is stressed or not stressed. While deep learning models have shown success in emotion recognition, simpler and interpretable machine learning models, such as Naive Bayes, Support Vector Machine, and Logistic Regression, remain underexplored in the context of stress detection using only feature-extracted facial images. Therefore, a comparison of these model's performance on stress classification is necessary to determine their viability and practicality in real-world applications. With this tool, stress can be detected early which can lead to timely interventions, improving quality of life and preventing adverse health outcomes. Additionally, traditional stress detection methods, such as surveys and biometric sensors, can be intrusive, expensive, or time-consuming [6][7]. This tool offers a non-invasive, cost-effective alternative that can be applied in real-time scenarios.

The rest of this paper is structured thus: Section 2 provides a detailed review of recent literature in the field of stress detection through 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 [8]. Among its various applications, image classification has garnered attention for its ability to identify patterns and classify data effectively [9]. This tech is also used in stress detection to detect it early and prevent adverse health outcomes [10][11][12]. This section is a summary of existing related papers previously published about detecting stress through facial image classification.

Researchers in [10] used a hybrid approach using 2 different datasets in parallel but complementary ways to achieve a more holistic understanding of stress. The datasets both are sourced from Kaggle and they are: the Facial Recognition Dataset which includes facial images and the other is Student Stress Factors Dataset which are behavioral and contextual factors, such as workload and deadlines. Their study used three models in total, one for image classification which is a custom Convolutional Neural Network (CNN), and 2 for the classification of the Student Stress Factors Dataset, which are Random Forest (RF) and Support Vector Machines (SVM). But mainly this study will focus on reviewing their image classification study. Before extracting features of their image datasets they preprocessed it to improve the robustness of the model by resizing, normalizing, and augmenting the images. The datasets were split into 80% for training, 10% for validation, and 10% for testing, and after this, they used their custom CNN to extract the features and passed through it to classify images into stress levels. Overall their custom CNN model got a validation accuracy of 92% and a testing accuracy of 90%.

Researchers in [12] used three Deep Convolutional Neural Networks (DCNN), which are VGG16, VGG19, and Inception-ResNet V2 in both extracting features and classifying the images after adding the DCNN classifier layers. They used datasets from three different sources which are from: Karolinska Directed Emotional Faces (KDEF), Extended Cohn-Kanade (CK+), and Net Images, which in total amount to 5235 images, which were then split to 80% for training, 10% for validation, and 10% testing. For feature extraction of the images, they used all three pre-trained models then they tested and added two types of classification layers for the final prediction of the image's class which are, Global Average Pooling (GAP) Classifier and Convolutional-Layer-Based Classifier. After fine-tuning, VGG16 with a convolutional layer-based classifier was the best-performing model with an overall accuracy of 89.6% and an f1-score of 89.7%.

Researchers in [11] achieve stress recognition by segmenting videos into 2-second clips and inputting facial image and facial landmark features using ResNet-18 as their model. The dataset used is the Yonsei Stress Image Database which includes over 2 million images of 50 subjects captured during various stress-inducing experiments, these stress tests were labeled: neutral, low stress, and high stress. The facial images of the 2-second clips were cropped from video frames and resized to 112×112 pixels, normalized, and blurred to address jitter effects, before embedding the images. The dataset was divided into training, validation, and testing sets in a ratio of 3:1:1 and a five-fold cross-validation method was employed to ensure robust performance evaluation. After classifying the images, the proposed method using ResNet-18 with spatial and temporal attention modules combined with facial landmark features achieved the best accuracy of 66.84% which outperformed alternatives such as VGG-16 and ResNet-50. This performance shows that it outperformed existing methods, including standard CNNs and handcrafted feature-based approaches..

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 [13], a file with 355 .jpeg files which are facial images categorized based on a person's emotional state which is Non-Stressed or Stressed. The Non-Stressed class includes emotions such as being happy and neutral, while the Stressed class includes emotions such as being sad and angry. Because of hardware limitations, this study uses 280 images with 84 Non-Stressed and 196 Stress 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 is stressed through facial images. This study uses a Deep Convolutional Neural Network (DCNN) which is Inception-V3, for feature extraction of the facial images.

Inception models were developed by a researcher [14] 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 [16]. 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 [17]. 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) [18][19]. And since the image datasets have higher resolution than the required input, the image is 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 [20]. After feature extraction using Inception-V3, the features are normalized to improve model training [21]. 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 facial images whether the person is stressed. To find the best classifier for this task, two classifiers, which include 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 [23][27]. The term ‘naive’ is used due to this algorithm's uncertain independence. With this, researchers in [24] 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 [27].

**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 [27].

**3.6 Model Evaluation Metrics:**

Evaluation measures are metrics used to assess the results of an experiment [25]. 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 [24].

(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 [27].

**Precision (PRE)** is computed by dividing all the true positive samples by the sum of the predicted positive samples and predicted negative samples [27].

(4)

A high precision score indicates strong class predictions, while a low precision score reflects weak class predictions [26].

**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 [27].

(5)

**F1-score (FS)** is the mean value for recall and precision. It offers an indicator of mistakenly graded results [24]. 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 [27].

(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, and confusion matrices.

**4.1. Model Performance**

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

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 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.

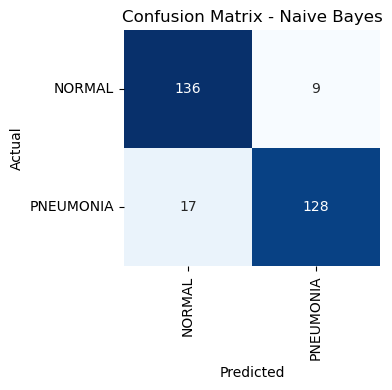
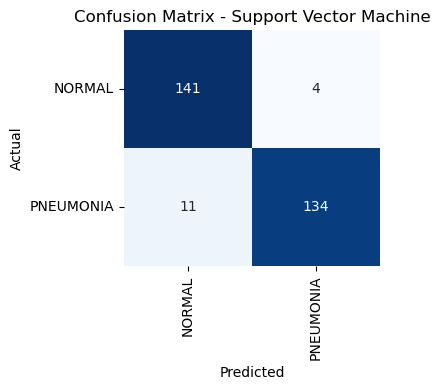
**Figure 2.** Graphical Performance Metrics

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, 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 exhibits significantly lower performance, with metrics around 90–94%. 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 outperforms NB in all performance metrics, which makes SVM the best model for identifying pneumonia in chest X-ray images. NB on the other hand still has good results overall but compared to SVM it is slightly behind. In conclusion, SVM provides the best overall performance, followed by NB.

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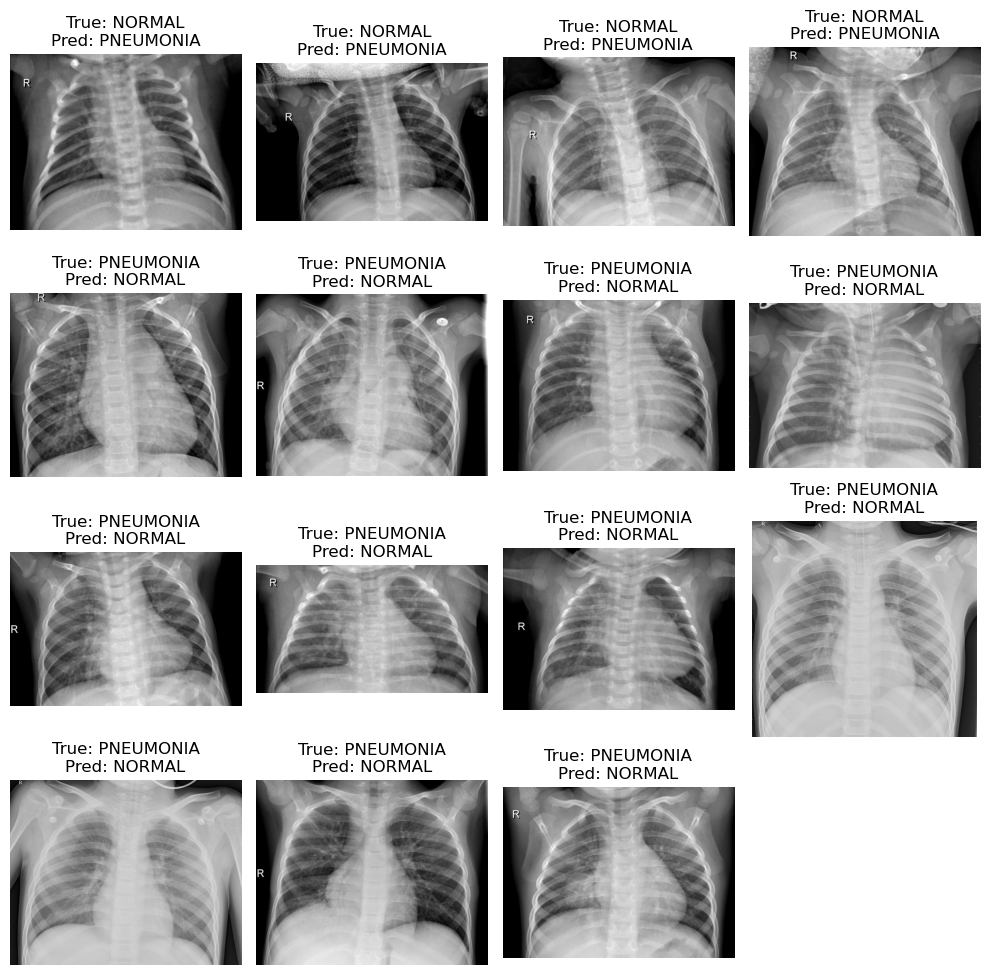
**Figure 3.** SVM Confusion Matrix

**Figure 4.** NB Confusion Matrix

The confusion matrix for the SVM model shows that it performs well in classifying both NORMAL and PNEUMONIA cases, with a slight tendency to miss some PNEUMONIA cases. Overall, the model shows strong predictive performance across all two classes.

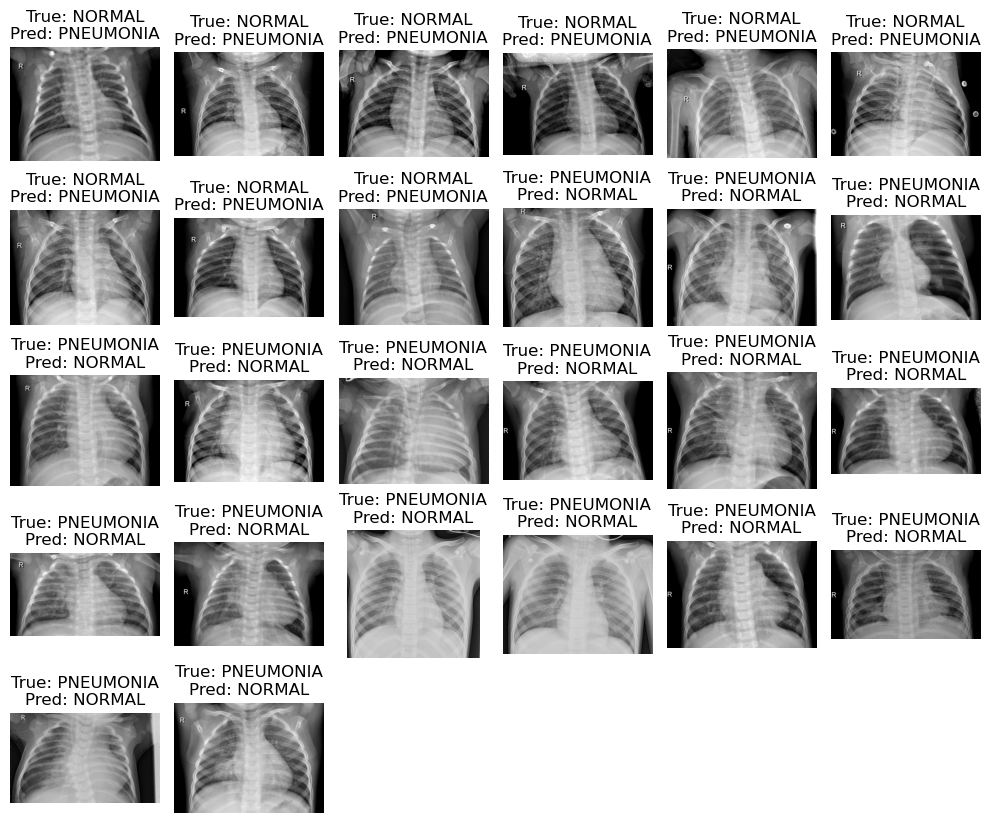
In contrast, NB still performs well in NORMAL and PNEUMONIA classification tasks, but it misclassifies more PNEUMONIA cases as NORMAL. There is a slightly higher precision for the NORMAL class compared to the PNEUMONIA class, but recall for PNEUMONIA is slightly better. Overall NB demonstrates good overall performance with an accuracy of 91.03%.

In general, SVM is the most effective model in identifying if a chest X-ray image has pneumonia, followed by NB.

**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 6.** 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, particularly on the recall metric.

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