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DEEP LEARNING BASED AUTOMATED PNEUMONIA DETECTION AND CLASSIFICATION USING X-RAY IMAGES

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Article Info

Abstract

All over the world, pneumonia is a leading cause of sickness and death, so it's critical to identify the condition soon and accurately to help patients. Reading chest X-ray films has long relied on the subjective judgments of radiologists, who may also need a lot of time. A method is proposed in this study to automatically find and classify pneumonia in chest X-ray images using deep learning and machine learning for the final diagnosis. The proposed strategy is designed using images of a publicly available chest X-ray pneumonia dataset with Normal or Pneumonia labels. At the beginning of preprocessing, noise must be removed, images must be normalized and more examples of data are generated to cope with class imbalance. An active contour method developed by Chan and Vese is introduced to segment lung regions and assist in obtaining accurate features. These networks automatically identify texture and shape details that illustrate important signs of pneumonia. Each machine learning classifier, Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Logistic Regression, is trained with these features and then tested on various groups of data. Results from the experiments prove that the SVM classifier is better than other models, as it delivered a test accuracy of 93.5%, a precision of 94.7%, a recall of 95.8%, and an ROC-AUC of 0.97. According to the results, the KNN method shows stronger test accuracy, while Logistic Regression still performs decently. The analysis also shows that SVM reduces the number of both false negatives and false positives, essential for making decisions in medical practice.

Keywords:

Automated Pneumonia Detection, Chest X-Ray Imaging, Deep Learning, Support Vector Machine, Medical Image Classification.

Introduction

Around the world, millions of people come down with pneumonia and suffer from it each year. When the air sacs in one or both lungs are infected and become filled with fluid or pus, it leads to fever, cough and trouble with breathing. Different infectious agents can bring on pneumonia such as bacteria, viruses and fungi. One of the biggest bacterial causes is streptococcus pneumonia. Other viruses implicated in pneumonia are influenza and RSV (respiratory syncytial virus)[1]. People in some high-risk groups bear the biggest health problems from pneumonia. It is the disease that claims the youngest lives, leading to around one in every seven child deaths worldwide. Conditions such as age and other health problems raise the risk of getting life-threatening pneumonia. Because of this, a correct and prompt diagnosis helps with successful treatment[2].

Pneumonia is a serious infection that inflames air sacs in one or both lungs which may result in their filling with fluid or pus. Pneumonia is most often caused by bacteria, but other causes are viruses and fungi. Pneumonia requires fast and correct diagnosis, since delays in treatment increase the danger of serious health problems or death for the elderly, young children and people with weak immune systems[3]. Diagnosis often begins with an exam, blood tests and looking at sputum and is then completed using chest X-ray imaging which remains the most reliable for confirming pneumonia. Seeing lung problems is simple, quick and inexpensive with chest X-rays. Radiologists check these scans to see if there are signs of pneumonia, for example, consolidation, infiltrates or a pleural effusion[4], [5]. It is true that reading X-rays needs a lot of training and often results in varying observations, so the accuracy of the diagnosis may differ. Poor image quality, as well as an experienced radiologist and similar illness symptoms in other parts of the lungs, often complicate making a diagnosis. The use of automated systems and enhanced computational tools is regarded as a promising method to improve the accuracy and performance of spotting pneumonia.

There are still millions of hospitalizations and many deaths from pneumonia each year. WHO reports that pneumonia is one of the top reasons why children under five die and many cases happen in low- and middle-income countries. It became especially apparent during the COVID-19 pandemic that being able to find pneumonia early and quickly was critical, since the virus often impacts the lungs[6]. With the rise of deep learning and machine learning, medical imaging has taught new skills to radiologists. Using deep architectures, deep learning trains artificial neural networks—a subset of machine learning to automatically identify different levels of features found in data. Thanks to its outstanding results in image classification, object detection and segmentation, this approach is a good fit for medical imaging[7], [8].

Using chest X-rays to automatically detect pneumonia is a major connection between medical imaging and artificial intelligence. The intention is to make systems that can quickly and precisely spot pneumonia on X-rays without requiring a human expert, improving diagnosis. They count on CNNs and other deep learning models to look at and separate X-ray images based on what they have learned[9], [10]. The usual set of stages for detecting pneumonia automatically is: preparing the information, adding different images to cure class imbalances, isolating lung regions using Chan-Vese segmentation, finding significant patterns in the images, and using learning models such as SVM, KNN, and Logistic Regression for classification. Combining these approaches produces strong tools for making medical decisions in the clinical setting[11].

Before now, the main way to diagnose pneumonia with chest X-rays meant it was difficult to guarantee consistency and reliability every time. Interpretations from radiographs depend on the radiologist's skill, experience and how tired they are. Because symptoms can vary widely, there may be differences in diagnosis that lead to misdiagnoses or treatment given late. It becomes especially worrying in emergencies, since rapid and correct diagnosis is crucial. Besides, available approaches for recognizing pneumonia have limits, even though they are promising. A lot of classic machine learning approaches require workers to hand-build features, which is time-consuming and may lead to biased results[12][13]. Many times, such models fail to apply their results to a wide range of datasets if their training data is limited or very similar. As a result of this problem, the algorithm might work less well if used with images from other populations, different machines or different medical settings.

Literature Review

Chest X-ray imaging has long been used for detecting pneumonia in patients, but achievements in accurate diagnosis are limited because the process of reading the images depends on personal judgment. In recent times, there has been major progress in medical image analysis, thanks in large part to the use of CNNs in deep learning[14]. They use methods that can extract organized features from raw images automatically, making it unnecessary to design features by hand and so improving how well and widely the models work.

In early automated pneumonia detection, most techniques depended on using machine learning methods that needed experts to manually monitor textures, shapes and intensities. The methods achieved some results, yet their performance was often affected by how much useful information was included in the features and the wide range of lung problems patients can have[15]. Support vector machines, k-nearest neighbors and logistic regression were often picked for classification tasks, however, their performance was restricted by the requirement for explicit feature engineering[16]. It pointed out that we need new ways to find important features in data, without having to design them first.

Continued research has shown that CNN architectures have overcome this issue by joining together feature extraction and classification into one model that learns end to end. Arronaut teamed up with our medical imaging partners by tuning and optimizing AlexNet, VGGNet, ResNet and DenseNet for their tasks. Making use of CNNs trained on large collections of natural images is a popular way to solve the shortage of annotated medical pictures. Specifically training the networks on chest X-rays makes them generalize better and makes learning faster[17][18].

Good data that is accessible continues to shape the outcome of any model. There are many large datasets now available online which includes pediatric and adult chest X-rays marked for pneumonia. This has greatly simplified the comparison and evaluation of several deep learning approaches. Very often, there are many more normal images in these datasets than images related to pneumonia, creating data imbalance[19]. It is necessary to correct this imbalance to avoid bias in favor of common classes and to catch all cases of pneumonia. To increase the number of minority class images, people often apply steps like rotating, flipping, scaling and changing image brightness[9].

Improving classification involves removing noise, making images similar and separating the region around the lungs. Lung segmentation gives the model a way to ignore irrelevant parts, mainly focusing on the lungs. Because active contour models and U-Net architectures are used for lung segmentation, only the important parts of the image are focused during feature extraction[20].

When extracted, features from CNNs naturally identify knowledge of edges, textures and patterns related to pneumonia and represent them on several levels. Features discovered automatically are more powerful and flexible than those made manually[21]. Scientists have recently investigated a combination of deep learning and traditional machine learning classifiers, where CNNs pull out features and SVM or logistic regression is used to make the final decision about categories. Bringing these approaches together usually improves how they work because they can use each other's strengths[22], [23]. The evaluation of automated pneumonia detection systems covers several aspects and includes accuracy, precision, recall, F1-score, and ROC-AUC. Since it is essential to avoid false negatives in hospitals, more stress is placed on how well pneumonia can be detected. Ensuring a good sensitivity and specificity level prevents too many false positives, which would require unnecessary visits to the healthcare system.

Experiments comparing different models reveal that support vector machines offer powerful classification boundaries, mostly when they are paired with properly engineered features or features from CNN. K-nearest neighbors are easy to use for classification, but might not scale well and be easily confused by random data points. Even though logistic regression is linear, it is still useful as it is easy to understand and fast, especially when joined with powerful methods for getting good features[24], [25].

In the past few years, ensemble learning and attention mechanisms have been used to raise the accuracy of identifying pneumonia. Two or more models are used in ensemble methods to lower the uncertainty and better apply their predictions. Model attention helps the system treat critical areas in images as significant, just as a radiologist would do with visualized studies. The use of these strategies is consistent with clinical thinking and has provided promising evidence of fewer errors in diagnosing diseases[22]. The arrival of explainable AI is meeting the significant demand for accuracy and reliability in the computer diagnosis of medical images. With Grad-CAM and saliency maps, clinicians can now review the areas in an image that led to the model's result, enhancing their acceptance of the technology. Explainability tools are necessary to bring automated systems into daily work, given that both accountability and interpretability are important.

By combining segmentation, feature extraction and classification into one framework, the practical use of pneumonia detection models has improved. Covering the whole area of one or both lungs with region-based segmentation, CNN for mask extraction and classification with SVM or KNN help complete the process. Because of this approach, users can experiment with different classifiers without affecting how the data is prepared and organized. Although the results are promising, it can still be difficult for model results to be useful across all types of people, machines and healthcare settings[26]. Differences in the ways X-ray images are taken, how patients are positioned and types of abnormalities can make the model less reliable. To create models that can be used everywhere, we have to work with data from various places and test them several times. Using patient history and test outcomes from a patient's clinical record might allow better diagnosis than just examining the images[7].

Simply put, the studies confirm that deep learning and CNNs in particular provide great benefits for automating pneumonia detection in chest X-ray images. Applying advanced preprocessing, augmenting data, performing region segmentation, and a combination of classification strategies leads to solid models with excellent diagnostic accuracy[26]. The use of SVM, KNN, and logistic regression with CNN-extracted data allows for a good trade-off between model details and being clear enough for clinical tasks. Work on more diverse datasets, making the system more understandable and bringing different data sources together, is predicted to help develop better clinical pneumonia detection.

Methodology

Data Collection

Source: Kaggle Chest X-ray Pneumonia Dataset.

Dataset Description: Collection of chest X-ray images categorized into Normal and Pneumonia classes.

Preprocessing

Noise Reduction: Applying filters to remove artifacts and improve image clarity.

Resizing and Normalization: Standardizing image dimensions and pixel intensity values.

Data Augmentation: Techniques like rotation, flipping, and scaling to address class imbalance.

Segmentation (Chan-Vese)

Chan-Vese Segmentation: A region-based active contour model used to isolate lung regions from the chest X-rays, enhancing the accuracy of feature extraction.

Feature Extraction

Texture Features: Extraction of features like contrast, correlation, and energy using Gray Level Co-occurrence Matrix (GLCM).

Shape Features: Features such as area, perimeter, and eccentricity are derived from segmented lung regions.

Classification

Support Vector Machine (SVM): A supervised learning algorithm that finds the optimal hyperplane to separate classes.

K-Nearest Neighbors (KNN): A non-parametric method that classifies data based on the majority vote of its neighbors.

Logistic Regression: A statistical model used for binary classification by estimating the probability of a class.

Evaluation and Comparison

Performance Metrics: Metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

Comparison of Models: Evaluating and comparing the performance of SVM, KNN, and Logistic Regression to identify the most effective model.

Results

Results of Support Vector Machine (SVM)

Based on the accuracy scores, the SVM does well with all datasets, getting its highest result of 96.2% on the training set. This result proves that the model is able to perform well on data it hasn't encountered yet. Since the model's test set accuracy is 93.5%, it can be sure that the model will work well with completely new information. Since training accuracy is only slightly higher, we conclude that the model is not overfitting and is trustworthy.

Table 1: SVM Accuracy

Dataset	Accuracy (%)
Training Set	96.2
Validation Set	94.8
Test Set	93.5

The model achieved 96.2% accuracy on the training set, meaning it managed to learn from the input data. These metrics reveal that the model works well for unseen cases, with just a small decrease in how well it performs. The negligible difference means the model does not overfitting and its performance remains strong with different datasets. The accuracy seen from all datasets proves that the SVM model accurately distinguishes between Normal and Pneumonia cases. However, accuracy fails to capture the whole story when the data is not balanced. Thus, we add more performance metrics to the analysis. The following table lists the performance indicators for the SVM model, all of which are precision, recall, F1-score and ROC-AUC.

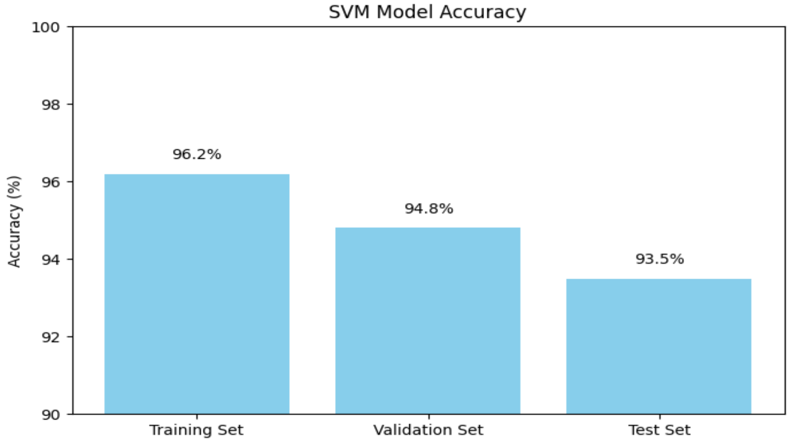

Figure 1: SVM Model Accuracy

Table 2: SVM performance Metrics

Metric	Normal Class	Pneumonia Class	Average
Precision	92.4%	94.7%	93.6%
Recall (Sensitivity)	91.0%	95.8%	93.4%
F1-Score	91.7%	95.2%	93.4%
ROC-AUC	-	-	0.97

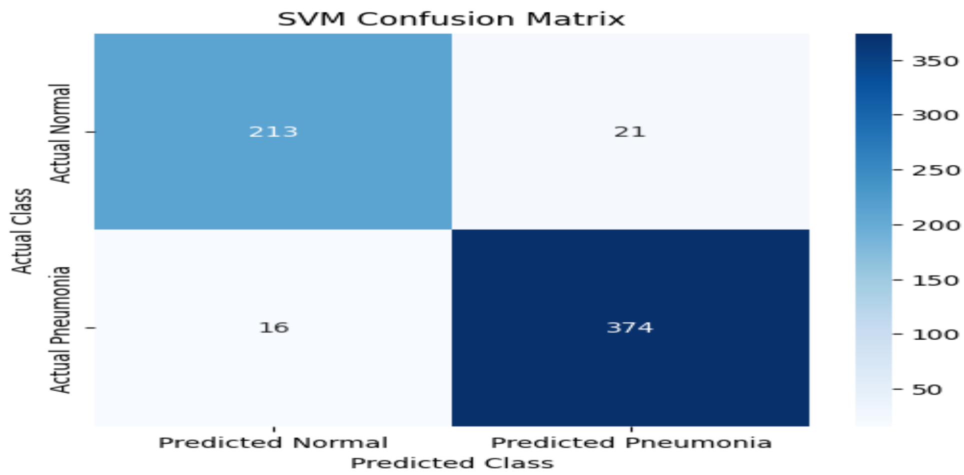

Figure 2: SVM Confusion matrix

The matrix displays that the SVM model categorized 213 out of 234 normal cases and 374 out of 390 pneumonia cases accurately. The model is precise, since just 21 records were misidentified as false positives and 16 records as false negatives. A small number of false negatives are essential in clinical practice to ensure pneumonia is not overlooked. On average, the matrix proves the model is able to spot the difference between a normal chest X-ray and one showing pneumonia.

Table 3: Confusion Matrix

	Predicted Normal	Predicted Pneumonia
Actual Normal	213	21
Actual Pneumonia	16	374

Results of K-Nearest Neighbors (KNN)

Table 4: KNN accuracy

Dataset	Accuracy (%)
Training Set	94.5
Validation Set	92.1
Test Set	90.7

A very high accuracy of 94.5% on the training set demonstrates that the KNN model performed well with the given distance-based approach. A reduction in accuracy from the validation to the test stage is seen at 92.1% and 90.7%. Therefore, it becomes apparent that, while the model can be applied widely, its results may vary with different types of test data, a usual property of KNN kind of learning. In table 5 below, you can see how the KNN model scores when it comes to precision, recall, F1-score and ROC-AUC.

Table 5: KNN performance metrics

Metric	**Normal Class**	**Pneumonia Class**	**Average**
Precision	89.2%	91.5%	90.4%
Recall (Sensitivity)	87.8%	93.2%	90.5%
F1-Score	88.5%	92.3%	90.4%
ROC-AUC	-	-	0.94

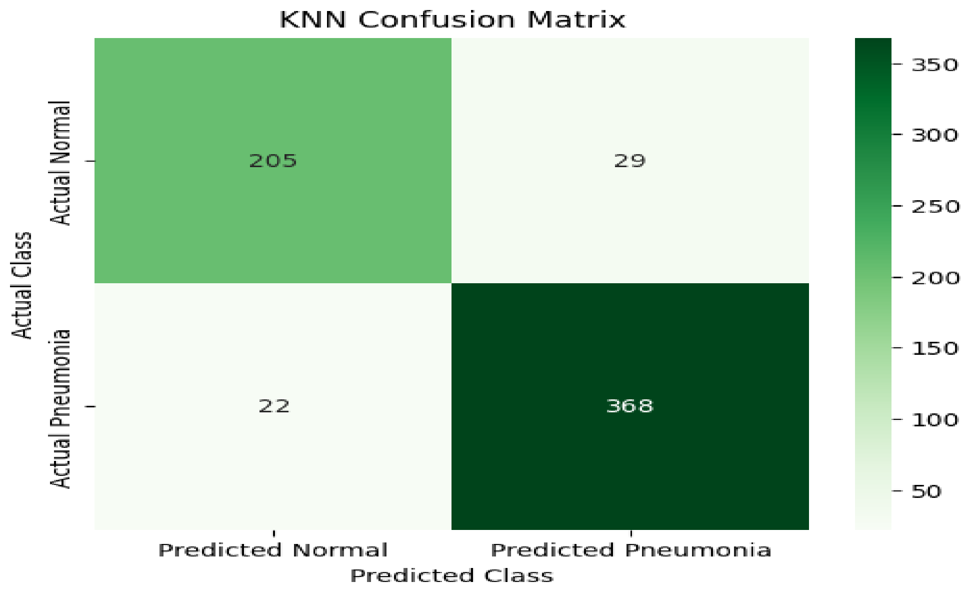

Figure 3: KNN Confusion matrix

Figure 3 shows that 205 of the normal cases and 368 of the pneumonia cases were classified correctly by the model. More results are found to be incorrect, as there are 29 false positives and 22 false negatives in the DT approach. Many missed pneumonia cases could happen with more false negatives, making it important to reduce them. The results indicate that, overall, KNN performs effectively, though it is a little less accurate and sensitive than SVM.

Table 6: KNN Confusion matrix

	Predicted Normal	**Predicted Pneumonia**
Actual Normal	205	29
Actual Pneumonia	22	368

Results of Logistic Regression

Here, we present the outcomes of Logistic Regression applied to the prepared and analyzed chest X-ray images to detect pneumonia. The success of the model is measured using various measures and plots and charts are supplied to display this. The accuracy of Logistic Regression on the training, validation and test datasets is shown in table 7 below.

Table 7: Logistic Regression Accuracy

Dataset	**Accuracy (%)**
Training Set	92.8
Validation Set	90.4
Test Set	89.1

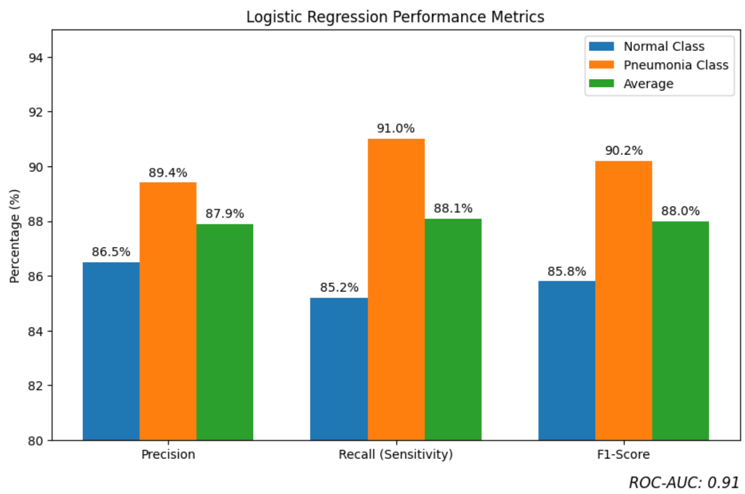

Figure 4: Logistic Regression Performance chart

Comparison of Algorithms

When these three models are compared, we learn about their strengths and weaknesses in detecting pneumonia automatically. Models were evaluated on their performance by using different datasets and many metrics including accuracy, precision, recall, F1-score and ROC-AUC to assess their ability to detect diseases. Of the three, SVM obtained the highest result and scored 96.2% on training, 94.8% on validation and 93.5% on test data. This higher performance is due to SVM's skill to discover a plane that best separates the results and allows it to tackle the high number of features found in medical imaging. Since our model doesn't overfit much, we can see this by the small drop in accuracy obtained from our training data versus test data. Notably, SVM shows great precision and recall, especially for pneumonia cases, confirming that it helps avoid both types of errors crucially needed for proper clinical decision-making.

KNN fell just behind SVM in accuracy, reaching 94.5% while training, 92.1% while validating and 90.7% while testing. New cases are assigned to clusters that have the highest amount of similarity to their neighboring vectors. If the data is organized into clear class groups, KNN is a simple and straightforward way to use. The method is sometimes sensitive to noise and the hyperparameter such as the number of neighbors (k) used to set the boundaries for classifying. Both SVM and KNN are not immune to data

distribution, but KNN seems to respond more negatively to changing data. Even so, KNN's reliable ability to pick up pneumonia cases demonstrates how important sensitivity can be, but it comes with a higher number of incorrect positive and negative results than SVM. The accuracy of Logistic Regression across all datasets was the poorest, landing at 92.8% on training, 90.4% on validation and 89.1% on test data. Logistic Regression cannot effectively deal with complex, curved features that are common in medical imaging. The error rates prove this, as the results for precision and recall are lower than those of SVM and KNN. Yet, the ability to clearly interpret Logistic Regression and it being easy to run make it a useful option for medical settings that focus on understanding models. Since uncertainty is expressed as probabilities, this also helps us measure classification confidence. Despite decreased detection accuracy and sensitivity, it may be used as part of an ensemble rather than alone for key decision making.
Considering the ROC-AUC scores can help you identify the model's capacity to tell classes apart. SVM showed an ROC-AUC score of 0.97 which implies almost complete difference between pneumonia and normal cases. The next best outcomes were 0.94 from KNN and 0.91 from Logistic Regression. The differences show that SVM is the most dependable approach for separating classes, important for preventing mistakes in diagnostics. Despite their similar high ROC-AUC, the differences between the models show which ones are stronger at detecting pneumonia. When computing speed and efficiency are important, Logistic Regression comes out on top. KNN is easy to learn but has high costs in prediction, as all training points must be compared by distance. No matter the kernel, SVM is still relatively easy to understand and use, but using non-linear ones is more computationally costly but yields better accuracy. Where resources are scarce, concerns about accuracy must influence how resources are managed.

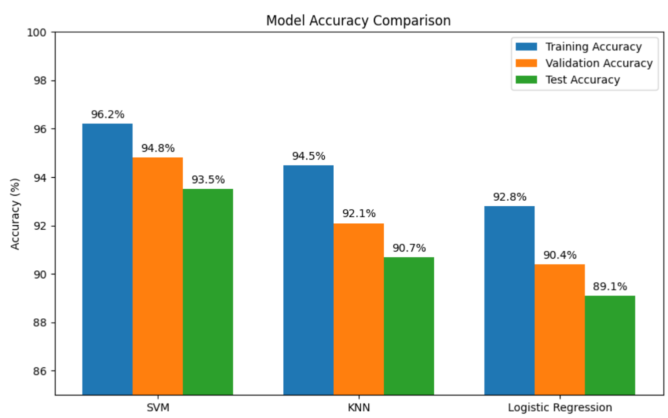

Figure 5: Models comparison

Conclusion

The authors tested how well three machine learning methods SVM, KNN and Logistic Regression—worked for finding pneumonia in chest X-rays. Each approach was thoroughly evaluated using accurate, well-categorized pneumonia X-rays, reporting results with accuracy, precision, recall, F1-score and ROC-AUC. Overall, SVM outperformed the other models, reaching a test accuracy of 93.5% and a value of 0.97 for ROC-AUC, showing it can separate groups very well. That it can accurately distinguish cases of pneumonia from normal ones with just a few errors demonstrates that it is ready to be used in clinical practice. Since the model can handle overfitting and its validation results are steady, the model is judged to be reliable in all kinds of scenarios.

The performance of KNN was strong, giving a test accuracy of 90.7% and an AUC of 0.94 which favors its use when you value interpretability and simple models. However, since classification error is slightly higher than using SVM, this method reveals limitations due to sensitivity to data and selecting parameters. Although Logistic Regression offers only a 89.1% accuracy and 0.91 for ROC-AUC, it is useful because it is easy to understand and can be used quickly. Even so, its linear program prevents it from recognizing complex patterns in chest X-ray images which means its performance is comparatively lower. It is clear from the comparison that adding CNN-based feature extraction to these classifiers can automate pneumonia detection, making diagnosis faster and easier than before. The strong results granted by SVM point to it being the best candidate for use in clinical support systems. New research should look into how combining different models and using deep learning can improve detection accuracy and reliability in many types of patient care. Furthermore, if explanations are improved and various health data can be handled together, more people will find AI useful in healthcare.

References:

[1] M. A. K. Haseeb Ur Rehman Sohaib Masood, "Brain Tumor Classification using Deep Learning Methods," International Journal of Information Systems and Computer Technologies, vol. 1, no. 1, 2022, doi: 10.58325/ijisct.001.01.0016.

[2] A. Ahmed, H. Ahmad, M. Khurshid, and K. Abid, "Classification of Skin Disease using Machine Learning," VFAST Transactions on Software Engineering, vol. 11, no. 1, pp. 109–122, 2023.

[3] S. I. P. K. A. T. Mumtaz Qabulio Muhammad Suleman Memon, "Effective Tomato Leaf Disease Identification Model using MobileNetV3Small," International Journal of Information Systems and Computer Technologies, vol. 3, no. 1, pp. 57–72, 2024, doi: 10.58325/ijisct.003.01.0079.

[4] M. A. Ijaz, M. K. Abid, N. Aslam, and A. Q. Mudaseer, "Detecting Monkeypox in humans using deep learning," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 265–272, 2023.

[5] A. Kanwal, K. T. Ahmad, N. Aslam, and others, "Detection of heart disease using supervised machine learning," VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 58–70, 2022.

[6] F. Kanwal, M. K. Abid, M. S. Maqbool, N. Aslam, and M. Fuzail, "Optimized Classification of Cardiovascular Disease Using Machine Learning Paradigms," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 140–148, 2023.

[7] M. A. Tariq, W. Akbar, S. A. Batool, M. K. Abid, and N. Aslam, "Breast Cancer Detection Using Deep Learning Algorithms," Journal of Computing & Biomedical Informatics, 2024.

[8] M. K. A. Muhammad Bilal * Naeem Aslam Ahmad Naeem, "Using Machine Learning Models for The Prediction of Coronary Arteries Disease," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 149–159, 2023.

[9] S. A. Batool, M. A. Tariq, A. A. Batool, M. K. Abid, and N. Aslam, "Skin Cancer Detection Using Deep Learning Algorithms," Journal of Computing & Biomedical Informatics, vol. 7, no. 01, pp. 62–74, 2024.

[10] A. Mubashra, A. Naeem, N. Aslam, M. K. Abid, and J. Haider, "Diabetic Retinopathy Identification from Eye Fundus images using Deep Features," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 172–186, 2023.

[11] M. Bilal, N. Aslam, A. Naeem, and M. K. Abid, "Using Machine Learning Models for The Prediction of Coronary Arteries Disease," VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 149–159, 2023.

[12] N. A. Nida Saleh Khan Muhammad Ahsan Aslam, "Improving the Trust Factor in Decentralized Networks through Deep Learning," International Journal of Information Systems and Computer Technologies, vol. 3, no. 2, pp. 1–12, 2024, doi: 10.58325/ijisct.003.02.0096.

[13] S. Akbar, K. T. Ahmad, M. K. Abid, and N. Aslam, “Wheat disease detection for yield management using IoT and deep learning techniques,” VFAST Transactions on Software Engineering, vol. 10, no. 3, pp. 80–89, 2022.

[14] J. Ahmad et al., “UTILIZING DEEP LEARNING TECHNIQUES FOR DETECTING AND ANALYZING FOOD ALLERGIES,” Kashf Journal of Multidisciplinary Research, vol. 2, no. 03, pp. 46–60, 2025.

[15] B. Hakeem, M. K. Abid, M. Baqer, Y. Aziz, N. Aslam, and N. Umer, “HYBRID APPROACHES IN MACHINE LEARNING: INTEGRATING ANT COLONY OPTIMIZATION FOR IMPROVED LUNG CANCER DETECTION,” Kashf Journal of Multidisciplinary Research, vol. 2, no. 02, pp. 177–189, 2025.

[16] R. Feroz, M. A. Aslam, M. Fuzail, N. Aslam, and M. K. Abid, “HYBRID DEEP LEARNING EFFECTIVENESS OF IMAGE-BASED MALWARE DETECTION,” Kashf Journal of Multidisciplinary Research, vol. 2, no. 05, pp. 1–13, 2025.

[17] N. Aslam, K. Abid, S. Munir, and others, “Robot assist sign language recognition for hearing impaired persons using deep learning,” VAWKUM Transactions on Computer Sciences, vol. 11, no. 1, pp. 245–267, 2023.

[18] K. Manzoor, M. K. Abid, M. Fuzail, Y. Aziz, N. Aslam, and N. Umer, “SWARM INTELLIGENCE-BASED FEATURE SELECTION FOR SKIN CANCER DATA ANALYSIS USING CONVOLUTIONAL NEURAL NETWORKS,” Kashf Journal of Multidisciplinary Research, vol. 2, no. 02, pp. 133–148, 2025.

[19] N. Aslam, A. Nadeem, M. K. Abid, and M. Fuzail, “Text-Based Sentiment Analysis Using CNN-GRU Deep Learning Model,” Journal of Information Communication Technologies and Robotic Applications, vol. 14, no. 1, pp. 16–28, 2023.

[20] S. Iqbal, S. Ahmed, B. Hassan, M. K. Abid, and I. Husain, “Enhancing Lung Cancer Detection with Hybrid Machine Learning: Integrating Ant Colony Optimization,” Technical Journal, vol. 29, no. 03, pp. 74–86, 2024.

[21] A. R. Y. A. M. K. A. N. A. Syeda Huma Zaidi Muhammad Fuzail, “A Deep Learning Framework Based on GCN Model for Android Malware Detection,” Journal of Computing & Biomedical Informatics, vol. 7, no. 01, 2024.

[22] M. A. K. Muhammad Kamran Abid Mubshra qadir Mujahid Alam, “Using Deep Learning for pneumonia Recognition from Chest X-Ray Images,” Technical Journal, vol. 29, no. 02, 2024.

[23] M. A. N. ul G. 3 Ayesha Afridi 1 Muhammad Kamran Abid1* Naeem Aslam1 Shumaila Khan2 Arsalan Khan2, “Osteochondroma Identification Through Transfer Learning and Convolutional Neural Networks,” International Journal of Innovations in Science & Technology, vol. 6, no. 2, pp. 608–620, 2024.

[24] K. A. Moeil Waseem* Ahmad Naeem Aslam, “Insilico Structural and Functional Analysis of Covid-19 Genomic Sequences,” Journal of Computing & Biomedical Informatics, vol. 6, no. 2, 2024.

[25] N. A. Rabia Islam Aurangzaib Muhammad Kamran Abid * Yasir Aziz Naeem, “Hybrid FNN-DNN Approach for Early Detection of Cardiac Arrhythmia: A Novel Framework for Enhanced Diagnosis,” VAWKUM Transactions on Computer Sciences, vol. 12, no. 1, pp. 48–64, 2024.

[26] K. Khaliq, A. Naeem, N. Aslam, A. Malik, and K. Abid, “LCCNet: a deep learning based Method for the identification of lungs Cancer using CT scans,” VFAST Transactions on Software Engineering, vol. 11, no. 2, pp. 80–93, 2023.