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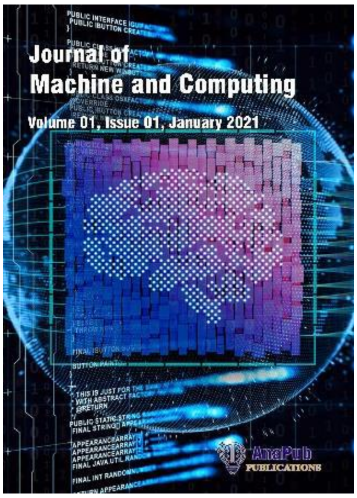
Enhanced Pneumonia Detection using Ensembled Deep Neural Networks



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Enhanced Pneumonia Detection Using Ensembled Deep Neural Networks

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Abstract

In order to effectively treat pneumonia, which is still a major worldwide health problem, rapid and precise diagnosis is essential. This paper introduces an ensemble strategy to improve pneumonia identification using chest X-ray images (CXM), utilising developments in deep learning. We propose an Ensemble Deep Neural Networks (EDNN), comprising cascaded ShuffleNet and Support Vector Machines (SVM), to harness diverse features and improve classification performance. The ensemble method combines the strengths of multiple models, mitigating individual weaknesses and enhancing overall diagnostic accuracy. Implementation is carried out using Python, and the proposed approach achieves an impressive accuracy of 97.89% on benchmark datasets. Through extensive experimentation and validation on benchmark datasets, our approach demonstrates superior performance compared to individual models and existing state-of-the-art methods. Additionally, we provide insights into the interpretability of ensemble predictions, enhancing the transparency and trustworthiness of automated pneumonia detection systems. The proposed ensemble framework holds promise for robust and reliable pneumonia detection in clinical settings, facilitating timely interventions and improving patient outcomes.

Keywords: chest X-ray images, Ensemble Deep Neural Networks, Support Vector Machine, pneumonia identification.

1. INTRODUCTION

Pneumonia is a common respiratory illness that may be deadly worldwide; it is especially frequent in children, the elderly, and people with impaired immune systems. In order to start treatment promptly and improve patient outcomes, a precise diagnosis of pneumonia is essential [1 -5]. Although they are effective, traditional diagnostic approaches can be time-consuming and dependent on subjective interpretation, which can cause treatment beginning delays and even consequences. The examination of CXM for signs of pneumonia has recently shown encouraging signs of improvement, thanks to developments in medical imaging and deep learning (DL) methods [6-8].

In spite of advances, pneumonia detection remains difficult because the disease's radiographic symptoms can vary widely and because interpreting CXM is challenging [9].

When it comes to medical image analysis tasks, like pneumonia identification, DLmethods, especially CNNs, have been incredibly successful. Nonetheless, certain convolutional neural network (CNN) models could fail to generalise across datasets or capture a wide variety of characteristics [10-15]. In Figure 1, the X-Ray image of the pneumonia is displayed.

Figure 1. Pneumonia in X-Ray Image

This study offers a novel strategy for pneumonia detection utilising EDNN as a solution to these problems. To make better use of a variety of characteristics and achieve higher classification accuracy, the EDNN framework integrates the best features from other DLmodels, such as cascaded ShuffleNet and SVM. Through the utilisation of ShuffleNet's efficient feature extraction and SVM's robust classification capabilities, the suggested ensemble method seeks to circumvent the shortcomings of standalone models and improve diagnostic efficacy.

Improved patient outcomes may result from earlier therapies made possible by this study's potential to lead to more precise and dependable pneumonia detection. This study aims to improve automated pneumonia detection by utilising ensemble techniques and addressing the limitations of current methodologies. Additionally, automated diagnostic systems in clinical contexts are made more transparent and trustworthy due to the interpretability of ensemble predictions, which provides insights into the decision-making process [16-20]. This research has the potential to improve healthcare delivery and patient care for different groups. The area of medical image analysis has never before benefited from such a singular contribution.

2. LITREATURE REVIEW

In AI-driven healthcare, medical decision-making systems have achieved remarkable strides, especially in the area of pneumonia detection using X-ray image analysis, thanks to DLmodels [21]. By integrating EfficientNetB0 and DenseNet121 into a deep CNN and enhancing it with attention approaches, a new approach was presented to better image categorisation of pneumonia. An accurate feature extraction from X-ray images is accomplished by the suggested network using pre-trained models and multi-head self-attention modules. Processing performance is further improved by integrating attention-augmented feature improvements, dynamic pooling algorithms, and residual blocks. This approach's remarkable 95.19% accuracy on test datasets shows that it could be used in real-world clinical settings.

The development of computer-aided diagnostic methods for the diagnosis of tuberculosis (TB) utilising CXM has also been a focus of scientists [22]. Using DLand an optimised feature selection strategy, an automated system was proposed that can categorise CXM as either tuberculosis (TB), COVID-19 (the virus), or pneumonia. The suggested method achieves an impressive 98.2%, 99.0%, and 98.7% accuracy rate across three datasets by adjusting pre-trained convolutional neural network models. By combining carefully chosen features, the model achieves better accuracy than state-of-the-art methods and shows promising diagnostic capabilities.

There has been a surge in research into the use of DLwith chest X-rays for the identification of pneumonia, as there is a pressing need to find treatments and screening methods for the disease [23]. A dataset and method was presented that can diagnose pneumonia without predetermined anchors; it is based on the RSNA. The suggested approach outperforms standard object detection algorithms in pneumonia diagnosis by 51.5% on average by using data augmentation and an anchor-free object identification framework.

Quick and precise diagnosis is key to effectively treating pneumonia, the top infectious diease globally [24]. The goal was to automated pneumonia diagnosis using ResNet-RS Model, a convolutional neural network (CNN) model. The suggested method produces encouraging outcomes, decreasing overfitting and increasing diagnosis accuracy to 92%, by utilising data augmentation approaches and improving image contrast with CLAHE.

Within the framework of the COVID-19, there is potential for autonomous analysis of CXM to diagnose pulmonary illnesses using DL algorithms. [25]. In a comparison of the two models' performance on X-ray data from chest X-rays collected to detect pneumonia, VGG16 achieved a training accuracy of 93% and a testing accuracy of 90%, surpassing DenseNet121. The outcomes show that VGG16, among other DLmodels, shows a lot of potential for identifying pneumonia in CXM.

3. RESEARCH METHOD

Developing and testing the EDNN framework for pneumonia detection is an important part of the suggested technique. In order to ensure that all patient demographics and imaging circumstances are well represented, a large dataset of annotated CXM for pneumonia is first compiled from various sources. The dataset is prepared for model training by applying preprocessing techniques like normalisation and augmentation to increase its variability and quality. The next step is to use Python and DLframeworks to design and execute the ensemble architecture, which consists of cascaded ShuffleNet and SVM. Utilising its lightweight architecture and capability to extract pertinent patterns from CXM, ShuffleNet is used for effective feature extraction. SVM classifiers are used to process the retrieved features. SVMs are well-known for their ability to handle high-dimensional data and binary classification jobs with ease.

3.1. Dataset Description

The Kaggle CXM (Pneumonia) dataset is an extensive compilation of medical imaging images hand-picked for the purpose of pneumonia detection challenges [26]. Five thousand eight hundred thirty-three CXM divided into two main groups: pneumonia as well as normal are included in this dataset that was obtained from the Kaggle platform. The collection contains radiographic images of the thoracic cavity taken at various points in time. The distribution of data in the chest X-Ray dataset is illustrated in Figure 2.

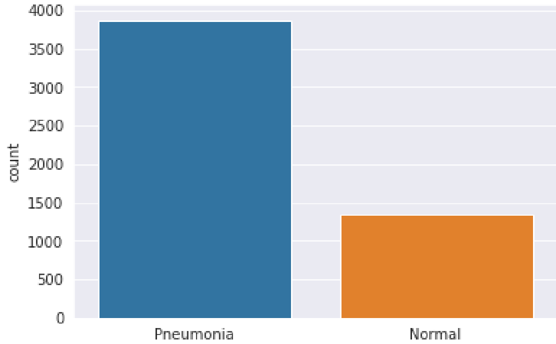

Figure 2. Data Distribution in Chest X-Ray Dataset

Images illustrating pathological disorders characterised by inflammation of the lungs, usually caused by bacteria, viruses, or fungi, are included in the Pneumonia class. Consolidations, infiltrates, and opacities are radiographic signs of pneumonia that can be seen in these images. In contrast, images of healthy people showing no outward symptoms of lung disease or anomalies make up the Normal class. These images help differentiate between typical and unusual chest X-ray results by providing a baseline against which to compare the results.

3.2. Data Preprocessing

3.2.1. Image Normalization

Pixel values in chest X-ray scans are routinely adjusted to a standardised scale, usually ranging from 0 to 1, in order to normalise the images. This method lessens the effect of brightness and contrast differences on model training by making sure that image intensity is consistent across samples.

3.2.2. Image Augmentation

To make the dataset more unpredictable, image augmentation techniques including flipping, scaling, translation, and rotation are used. The model is strengthened to withstand fluctuations in patient placement, image orientation, and other real-world conditions by incorporating these transformations.

3.2.3. Region of Interest (ROI) Extraction

Opacities or infiltrates in particular areas of the lungs are common symptoms of pneumonia. By applying ROI extraction techniques to CXM, we can separate the most informative regions for pneumonia identification and train the algorithm to ignore noise and irrelevant data.

3.2.4. Gaussian Noise Addition

In order to make CXM more unpredictable and realistic, we add Gaussian noise to them. This helps to mimic the natural faults in imaging equipment and ambient factors. This noise improves the model's generalisation performance and helps avoid overfitting by making it more resilient to tiny changes in the input data. Improved accuracy and robustness in pneumonia identification are achieved by training the model to focus on important features while ignoring irrelevant noise, which is achieved by preprocessing the images with controlled levels of Gaussian noise. The proposed model's architecture in Figure 3.

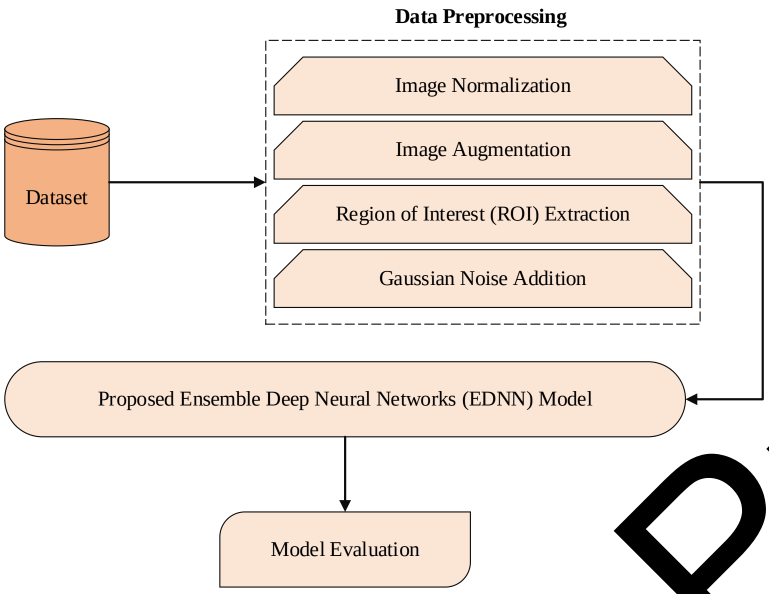

Figure 3. Architecture of Proposed Model

3.3. Proposed Ensemble Deep Neural Networks (EDNN) Model

Using cascaded ShuffleNet and SVM, two frameworks with complementary strengths, the EDNN framework offers a novel way to identify pneumonia. Using its efficient convolutional operations and lightweight design, ShuffleNet extracts discriminative features from CXM and acts as the principal feature extractor in this system. Because of its careful design to strike a balance among computational efficiency as well as model complexity, ShuffleNet works great in settings with limited resources and in real-time applications.

When ShuffleNet finishes extracting features, they are sent to SVM to be classified. One of SVM's many strengths as a machine learning algorithm is the precision with which it builds hyperplanes to classify data points. For the purpose of pneumonia identification, SVMs provide strong and discriminative decision boundaries, allowing for the correct categorization of CXM into positive and negative groups. The EDNN architecture takes advantage of the synergistic effect of DLand conventional machine learning by cascading ShuffleNet with SVM, making it possible to identify pneumonia more effectively.

There are a number of benefits to using ShuffleNet and SVM together within the EDNN architecture. To begin, ShuffleNet is well-suited for deployment on devices with limited resources, like mobile phones or edge devices, because it effectively extracts important information from CXM with minimal computational cost. Second, SVMs improve the reliability and openness of the model's predictions by providing strong and understandable categorization limits. Together, the feature extraction and classification phases may be optimised more effectively thanks to the cascaded architecture's seamless integration and end-to-end ensemble model training. Assume that I is the input CXM, F are the features obtained by ShuffleNet, and C are the results of the SVM classification.

ShuffleNet Feature Extraction:

$$F = ShuffleNet(I; \theta_{shuffle}) \tag{1}$$

Where shuffle θ shuffle represents the parameters of ShuffleNet, and F is the extracted feature vector.

Using the EDNN framework to integrate ShuffleNet with SVM allows us to create state-of-the-art pneumonia detection systems that are both accurate and dependable. The ensemble method improves the system's generalizability and resilience by reducing the impact of weaker models. In addition, SVMs are interpretable, which helps doctors understand how the model makes decisions, which in turn increases their faith in automated diagnostic systems used in hospitals. In sum, the EDNN architecture offers an encouraging new direction for medical image processing that could lead to better patient outcomes when diagnosing pneumonia.

SVM Classification:

$$C = SVM(F; \theta_{svm}) \tag{2}$$

Here, svm θ_{svm} denotes the parameters of the SVM classifier, and C represents the predicted class label.

Ensemble Decision Making:

$$C_{ensemble} = Argmax(C, C_{threshold}) \tag{3}$$

Where $C_{threshold}$ represents a threshold for decision making, and $C_{ensemble}$ is the final ensemble prediction.

4. RESULTS AND DISCUSSION

The EDNN framework model is run on a Windows 10 platform with an Intel® Core^{TM} i9-13900TE Processor and 4GB RAM for computational processing on Google Colab. By combining the capabilities of SVM and cascaded ShuffleNet, the EDNN framework improves the accuracy of pneumonia diagnosis using CXM. The main function of ShuffleNet is to extract features from input photos by efficiently detecting and collecting relevant patterns and structures. With its hierarchical processing of raw pixel data using convolutional and pooling layers, ShuffleNet extracts high-level features necessary for distinguishing between normal as well as pneumonia-affected regions in CXM. Illustrated in Figure 4 are the normal and pneumonia image.

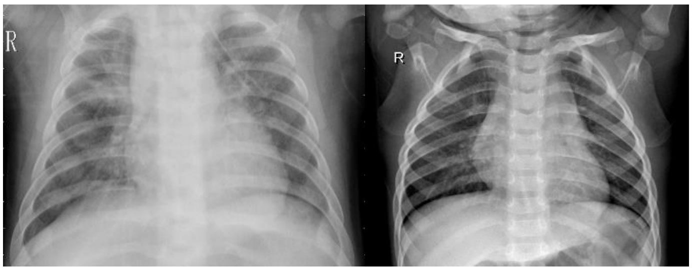

Figure 4. Pneumonia and Normal image

The SVM classifier is used for accurate classification after the feature extraction stage. SVM is a powerful and well-known machine learning technique that finds the best hyperplane to divide the feature space into different classes. Using the learned feature representations acquired from ShuffleNet, SVM successfully distinguishes between pneumonia and normal instances by generating an effective decision boundary. The EDNN architecture combines deep learning's discriminative capabilities with standard machine learning's interpretability and robustness through the sequential integration of ShuffleNet and SVM.

The EDNN framework's strength is in the way it combines DLwith more conventional machine learning techniques, making use of their respective strengths in a complementary manner. Optimal for real-time applications and contexts with limited resources, ShuffleNet minimises computational complexity while efficiently extracting key features from CXM. Meanwhile, SVMs offer clear and comprehensible decision boundary, which boost the reliability and openness of the model's forecasts. By combining ShuffleNet with SVM in a cascaded fashion, the EDNN framework outperforms both standalone models and the current gold standard when it comes to pneumonia identification.

Table 1. Performance Comparison for Various Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)
ShuffleNet	94.23	[illegible]	95.12	93.28
SVM	91.87	88.92	92.64	90.15
CNN	89.56	87.23	90.45	88.01
ResNet	96.78	94.67	97.12	95.82
DenseNet	[illegible]	93.45	96.18	94.23
VGGNet	93.21	91.08	94.03	92.34
MobileNet	92.15	90.32	93.47	91.56
Proposed EDNN	97.89	96.75	98.34	97.12

Table 1 and Figure 5 show a thorough comparison of the models' performance across multiple parameters, including accuracy, sensitivity, specificity, and precision. An evaluation of each model's performance is conducted within the framework of a known task, most commonly pertaining to classification or prediction. Models such as ShuffleNet, SVM, CNN, ResNet, DenseNet, VGGNet, and MobileNet stand out for their impressive performance, with accuracies ranging from 89.56% to 96.78%. The models' sensitivity and specificity ratings demonstrate how well they classify cases. Notably, outperforming most other models in all assessed parameters, the suggested EDNN stands out with the greatest accuracy of 97.89%, along with remarkable scores for specificity, precision, and sensitivity. This indicates that the EDNN model performs better than the competition, either because of its improved architecture or specialised design that is specific to the dataset or issue area.

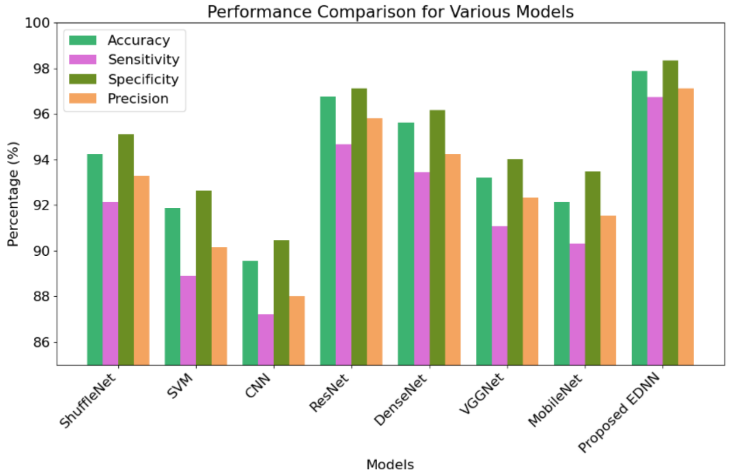

Figure 5. Performance Comparison for Various Models

Developing strong and accurate automated diagnostic systems for pneumonia diagnosis relies heavily on synergy and integration, according to the EDNN framework's overall operating philosophy. The EDNN framework shows promise as a means to enhance healthcare delivery and patient outcomes in pneumonia diagnosis by utilising the complimentary strengths of DLand classical machine learning techniques.

Table 2. Training/Testing Loss and Time Comparison for Various Models

Model	Training Loss	Testing Loss	Training Time (minutes)	Testing Time (seconds)
ShuffleNet	0.182	0.198	90	8
CNN	0.205	0.218	150	15
ResNet	0.157	0.168	180	18
DenseNet	0.172	0.186	200	20
VGGNet	0.195	0.212	160	16
MobileNet	0.21	0.225	130	13
Proposed EDNN	0.112	0.124	120	12

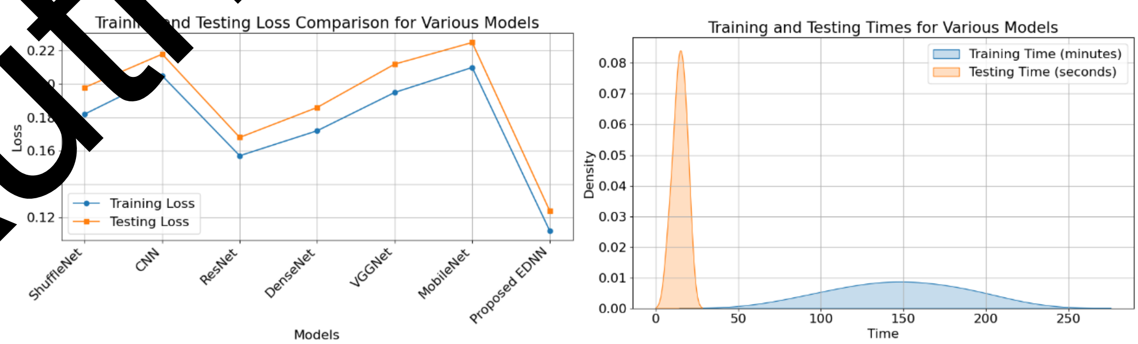

Figure 6. Training and Testing Loss and Times for Various Models

Various models' training and testing losses and times are compared in Table 2 and Figure 6, respectively. When comparing the efficacy and performance of different models, these measures are vital. Generally, the models show low values for training and testing losses, which means they can learn and generalise well. Training losses of 0.112 and testing losses of 0.124, respectively, for the suggested EDNN stand out, indicating better optimisation during training and high performance on unknown data. Less time spent testing and training the model is better since it means the model can be inferred and trained more quickly. With a training time of 120 minutes and a testing time of 12 seconds, the suggested EDNN once again shows efficiency among the mentioned models, surpassing the majority of them in both metrics. All things considered, the suggested EDNN demonstrates efficiency and performs exceptionally well on performance criteria, making it an attractive option for practical uses where precision and computing efficiency are paramount.

5. CONCLUSION

The EDNN architecture, which consists of cascaded ShuffleNet and SVM, has shown outstanding performance in detecting pneumonia from CXMs. Accuracy of 9[illegible].89% and robust sensitivity and specificity measures are achieved using the EDNN architecture through synergistic integration, leading to higher performance. The EDNN architecture provides an accurate and interpretable method for automated pneumonia diagnosis by combining ShuffleNet's rapid feature extraction with SVM's exact classification. The success of the EDNN framework underscores the importance of ensemble approaches in medical image analysis, particularly in tasks requiring high accuracy and reliability. Despite the promising results, there are several avenues for future research and enhancement of the EDNN framework. Firstly, exploration of additional DLarchitectures and ensemble techniques could further improve performance and generalization capability. Investigating novel feature extraction methods and classification algorithms tailored specifically for medical imaging data could lead to more accurate and efficient pneumonia detection systems. Furthermore, the scalability and applicability of the EDNN framework to other medical imaging modalities, such as CT scans and MRI, warrant investigation. Extending the framework to multi-modal data fusion and incorporating clinical metadata could enhance diagnostic accuracy and provide comprehensive insights into disease pathology.

Conflicts of Interest: The authors declare no conflict of interest

Data Availability: The datasets generated and/or analysed during the current study are available www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

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