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Evaluating Diagnostic Thresholds for Pneumonia Severity Using HOG Features and Deep Learning Models

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Abstract*— Pneumonia severity diagnosis is vital for effective and efficient patient treatment and management. This study evaluates the efficacy of different diagnostic thresholds for pneumonia severity using Histogram of Oriented Gradients (HOG) features and deep learning models on chest X-ray images. Utilizing the Kaggle chest X-ray dataset, HOG feature extraction was applied, followed by Pearson correlation to compare a randomly selected X-ray with pneumonia images. Three diagnostic thresholds were used for severity diagnosis. The results demonstrated that all thresholds performed well in detecting moderate cases, with Threshold1 and Threshold2 both achieving an accuracy of 89% and an F1-score of 0.94. Threshold3 had an accuracy of 66% and F1-scores of 0.62 and 0.94 in identifying mild and moderate cases, respectively. The evaluation metrics included accuracy, precision, recall, and F1-score. These findings suggest that careful selection of diagnostic thresholds can significantly impact the accuracy and reliability of pneumonia severity diagnosis using deep learning models, with potential applications in clinical settings.

***Keywords*— Pneumonia, Severity, HOG, Pearson Correlation, Diagnostic thresholds, Deep Learning Model**

I. INTRODUCTION

Disease diagnosis is necessary to confirm the presence or absence of an ailment, however, knowing the severity level of the disease is an important aspect of medical evaluation to assists the healthcare providers in ascertaining the intense of the patient's disease condition. Pneumonia, a deadly a form of acute lower respiratory tract infection disease that affects one or both air sacs of the lung causing it to be filled with pus in place of air, it has no regards for age, sex, race or gender, it can affect anybody, having most prominent effect on children aged 5 years and below and elderly adults aged 65 years and above. Pneumonia, one of the differential diagnosis of almost all respiratory diseases including the dreaded covid-19 that turned the world upside down (Kickbusch *et al.*, 2020; Ortiz-Toro *et al.*, 2022).

Usually caused by bacteria, virus, or fungi, pneumonia, depending on the causative agents is having disease severity ranges from mild which can be treated as outpatients to severe which might require hospitalization. Hence, the disease severity is classified into levels such as mild, moderate, and severe used in assisting the healthcare providers in monitoring disease progression over time, determining appropriate treatment plan, predicting potential complications and outcomes, allocating healthcare resources effectively and enhancing

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communication among healthcare providers. With accurate pneumonia severity diagnosis, radiologists and by extension pneumologists will be able to provide appropriate intervention to each patient needs and adjust treatment plans as the condition changes.

II. RELATED WORK

Bunch of researchers have carried out studies in disease diagnosis, Jaiswal *et al.*,2019 presented a Mask-RCNN deep neural network model for pneumonia identification and discerning the role the size of the lung image played in the proposed model. Chidambaram *et al.*, 2020 carried out review of some published articles from reputable academic database such as Embase, WHO, and PubMed, in determining the radiological, laboratory, clinical, demographic factors linked with Covid-19 severity and mortality. As a result of deep learning ability to automate the classification of chest abnormalities and reduce the high pneumonia mortality and morbidity rates, Li *et al*. (2020) conducted an organized analysis and compilation of deep learning diagnostic algorithms for detecting and classifying pneumonia using chest radiograph images. Nur-A-Alam *et al*. (2021) utilized deep learning with CNN in detecting COVID-19 disease on X-ray images. Additionally, Tahir et al., 2021 suggested a unique and systematic method for COVID-19 infections evaluation from chest X-ray images through lung segmentation and identification constrained to the infected area.

Artificial intelligence (AI), a branch of computer science that attempt to model the computer system to emulate human by finding solutions to complex problems such as knowledge, reasoning, perception and communication in ways most intelligent people do. AI has shown enormous success in assisting healthcare providers in faster and accurate disease diagnosis from radiograph images such as X-ray and MRI. Due to the use of deep learning, an advanced type of machine learning that utilizes multi-layered neural networks motivated by the structure and functioning of human brain to make decisions based on complex data patterns and offers cutting-edge capabilities in a number of fields, including disease diagnosis; with the aim to develop computational models that can process and analyse data in a manner that emulates the human brain's processing mechanisms, deep learning demonstration of excellent proficiency in tasks such as image classification has surpassed the capabilities of human experts, showing their exceptional ability in accurately identifying and categorizing complex visual patterns, a lot of researchers have designed and developed diagnostic models that can be used in the diagnosis of pneumonia using chest X-ray images.

Automated blood parasite detection model aiming to enhance the accuracy of malaria diagnosis was designed by Alnussairi *et al*. (2022) using MobileNetV2, ResNet50, and VGG19 convolutional neural network (CNN) pre-trained models, which were evaluated on National Institute of Health (NIH) malaria dataset. Deep learning approach was utilized by Boyadzhiev *et al*., 2022 to determine a patient pneumonia status through X-ray images or CT scans. A deep learning model that utilized a dual phase sequential training for detection and severity prediction of COVID-19 was suggested by Sharma *et al*. (2022). Five Deep Learning models: VGG16, InceptionV3, Xception, ResNet50, and Convolution Neural Networks (CNN) were built and comparative analysis was carried out for the diagnosis of Covid-19 on the Google Colab GPU, the models were trained for 100 epochs on a total of 1686 images of chest X-rays and CT scans. The model with the Xception algorithm is the most accurate one in determining the presence of the disease with an accuracy of 81% and 89% on CT scans and chest X-ray images respectively.

Elbarougy *et al*. (2023) developed an intelligent COVID-19 diagnostic system with higher accuracy and low complexity using combination of HOG extracted features with CNN, obtaining 96.6% accuracy on 3,886 X-ray images, which were partitioned into training, testing, and validation subsets. Prakash et al. (2023) introduced a combined ensemble learning method for the classification of paediatric pneumonia into Normal and Pneumonia using deep learning by extracting features from X-ray images. Zhang et al. (2023) employed a deep learning approach based on Convolutional Neural Networks (CNNs) to develop a model capable of detecting pneumonia cases from chest X-ray image data, with the aim of reducing if not totally eliminate high number of pneumonia patients. All the reviewed articles on pneumonia diagnosis were based on binary classification which is detecting the presence or absence of pneumonia, no model has been implemented to classify already confirmed pneumonia radiograph images into severity levels to provide appropriate treatment plan, predicting potential complications and outcomes, allocating healthcare resources effectively and enhancing communication among healthcare providers.

III. DIAGNOSTIC THRESHOLDS FOR PNEUMONIA SEVERITY

The dataset and the Deep Learning Model for Pneumonia Severity Diagnosis architecture proposed by Olatunde *et al.*, 2024 was utilized in the diagnostic threshold models for pneumonia severity classification which entails X-ray images preprocessing, extraction of HOG feature from the preprocessed images and utilized Pearson correlation for target categorization, and convolutional neural network for classification. The dataset was split as shown in Table 1.

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TABLE 1
INSTANCES OF IMAGES PRESENT IN EACH CLASS

Normal	1341		
Pneumonia	3875	Train (70)	Testing (30)
		2713	1163
Total Images	5216		

A. Target Categorisation using Pearson' Correlation

To evaluate the intensity of the relationship between Normal X-ray images and Pneumonia X-ray images, the feature vectors from both Pneumonia and Normal X-ray images are passed through Pearson correlation, and the strength magnitude between a Normal X-ray image selected randomly and Pneumonia X-ray images are computed as shown in Equation (1) employed in describing the strength and direction of an association between variables.

$$s = \frac{\sum(n_i - \bar{n})(p_i - \bar{p})}{\sqrt{\sum(n_i - \bar{n})^2 \sum(p_i - \bar{p})^2}} \qquad (1)$$

Where s= correlation strength; n_i= values of a randomly picked extracted Normal X-ray image HOG features vector; $\bar{n}$ = mean value of the Normal X-ray images features vectors; p_i= values of the extracted pneumonia X-ray image HOG features vector; $\bar{p}$ = mean of the value of pneumonia X-ray images features vectors.

A list of all files in the 'Normal' folder is gotten, and randomly selecting any Normal X-ray image, the Pearson correlation between the Normal image feature vector and all Pneumonia hog feature vectors is computed, which is used in classification into severity classes. Samples of the Pneumonia Severity Classification labels is shown in Figure 1

From the reviewed literature, there is clear indication that there is no pneumonia severity classification model developed, hence, using the correlation strength s, three different thresholds according to equations (2) - (4) were picked in developing the severity models by reclassifying the pneumonia images into severity groups, which were trained and evaluated.

$$f(s_1) = \begin{cases} Severe & if\ s < 0.4 \\ moderate & if\ 0.4 \le s < 0.6 \\ mild & if\ s \ge 0.6 \end{cases} \qquad (2)$$

$$f(s_2) = \begin{cases} Severe & if\ s < 0.3 \\ moderate & if\ 0.3 \le s < 0.6 \\ mild & if\ s \ge 0.6 \end{cases} \qquad (3)$$

$$f(s_3) = \begin{cases} Severe & if\ s < 0.2 \\ moderate & if\ 0.2 \le s < 0.5 \\ mild & if\ s \ge 0.5 \end{cases} \qquad (4)$$

Where

$f(s_1)$, $f(s_2)$, $f(s_3)$ represent the pneumonia severity function for Threshold1, Threshold2, and Threshold3, the computed correlation coefficient between a randomly picked 'Normal X-ray image' and 'Pneumonia X-ray images' respectively.

The three diagnostic threshold models were compiled individually using Categorical_crossentropy as Loss Function, Adam optimizer, and Accuracy as Metrics. The models were trained for 10 epochs, with 2712 training data consisting of three classes ('Mild', 'Moderate', 'Severe') in 32 Batch size, and tested with 1163 test data, also of three classes. Sample of the model classification labels is shown in Figure 1.

Each Model is trained, and the result discussed, analysed and evaluated. The input to the model is the output of the Pearson correlation computation, and all the deep learning models for Pneumonia Severity diagnosis were trained using the following architectural settings: two Conv2D layers, the first with 16 filters, a kernel size of (3, 3), ReLU activation, and a stride of (1,1); the second with 32 filters, a kernel size of (3, 3), ReLU activation, and a stride of (1,1), followed by a MaxPooling2D layer with a pool size of (2, 2).

Two more Conv2D layers were added, the first with 16 filters, a kernel size of (2, 2), ReLU activation, and a stride of (1,1); and the second with 32 filters, a kernel size of (2, 2), ReLU activation, and a stride of (1,1), followed by another MaxPooling2D layer with a pool size of (2, 2). For the fully connected layers, the model used a Flatten layer to convert 2D feature maps into a 1D vector, followed by two Dense layers, one with 100 units and ReLU activation, and another with 50 units and ReLU activation. A Dropout layer was included with a rate of 0.5 for regularization. Finally, the output layer was a Dense layer with 3 units and Softmax activation.

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During the training process, the model underwent 10 epochs, each representing a full iteration over the entire dataset. During these epochs, training loss, that measures the average error across all training samples for each epoch, and the training accuracy, which measures the proportion of correct predictions on the training dataset were monitored. These metrics give an overview of the model's learning progress and its ability to understand the training data.

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'MODERATE',   'MODERATE',   'MODERATE',   'MODERATE',   'MODERATE',   'MILD',
'MODERATE',   'MODERATE',   'SEVERE',   'SEVERE',   'MODERATE',   'MODERATE',
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'MODERATE',   'SEVERE',   'MILD',   'MODERATE',   'MODERATE',   'MODERATE',
'MODERATE', 'MODERATE']
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Figure 1. Sample Pneumonia Severity Classification Labels

B. Pneumonia Severity Diagnostic Threshold1 Model

The Pneumonia Severity Threshold1 model was based on Equation (2), and was implemented using the stated algorithm. The loss and accuracy performance metrics of the training and validation of each epoch during the training of Diagnostic Threshold Pneumonia Severity Model1 as summarised in Table 2, and the model classification report is shown in Figure 2.

TABLE 2
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD1 TRAINING RESULT

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.4105	0.8787	0.3900	0.8899
2	0.3770	0.8897	0.3718	0.8899
3	0.3518	0.8897	0.3550	0.8899
4	0.3334	0.8897	0.3358	0.8891
5	0.3275	0.8868	0.3344	0.8891
6	0.2914	0.8960	0.3275	0.8865
7	0.2741	0.8975	0.3363	0.8891
8	0.2444	0.9019	0.3901	0.8891
9	0.2337	0.9115	0.3665	0.8676
10	0.2020	0.9211	0.3669	0.8882

TABLE 3
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD1 CLASSIFICATION REPORT

Classes	Precision	Recall	F1-Score	Support
0 (Mild)	0.40	0.05	0.09	117
1 (Moderate)	0.89	0.99	0.94	1035
2 (Severe)	1.00	0.09	0.17	11
Accuracy			0.89	1163
Macro avg	0.76	0.38	0.40	1163
Weighted avg	0.85	0.89	0.85	1163

Pneumonia Severity Diagnostic Threshold1 Model Training Summary

The Pneumonia Severity Diagnostic Threshold1 Model recorded 92.11% and 88.82% as the highest training and validation accuracies respectively, having an overall accuracy of 89%. as shown in Table 2 performed well

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for class 1 (Moderate), but not as well for classes 0 (Mild) and 2 (Severe), which might be reason of the high pneumonia mortality rate as a result of moderate severity progressing to 'Severe' severity level because of lack of adequate prioritization of the limited resources by the health facilities. Generally, Pneumonia Severity Diagnostic Threshold1 Model recorded 92.11% and 88.82% as the highest training and validation accuracies respectively, having an overall accuracy of 89%. The diagnostic threshold1 accuracy score and value loss is as shown in Figure 2 and Figure 3 respectively.

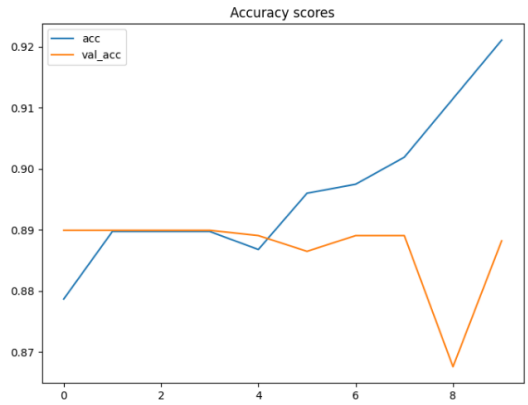

Figure 2. Pneumonia Severity Diagnostic Threshold1 Accuracy score

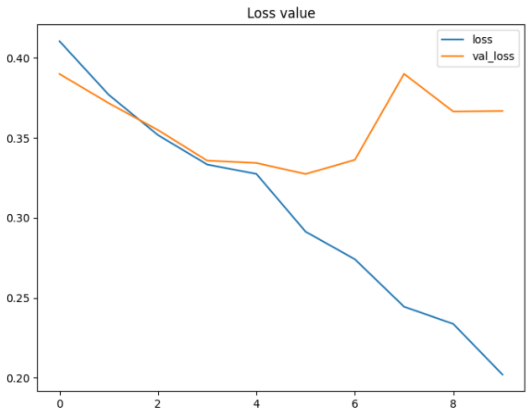

Figure 3. Pneumonia Severity Diagnostic Threshold2 Loss value

C. Pneumonia Severity Diagnostic Threshold2 Model

The Pneumonia Severity Diagnostic Threshold2 Model was based on Equation (3), and developed using the architecture described above. The summary of Pneumonia Severity Diagnostic Threshold2 Model training was represented by Table 4 showing the detailed analysis of the loss and accuracy metrics computed for both the training and validation datasets across each epoch during the training process of Pneumonia Severity Classification Model 2.

Generally, Pneumonia Severity Diagnostic Threshold2 Model exhibited robust performance achieving high accuracy scores on both the training and validation datasets having highest training accuracy of 95.59%, highest test validation accuracy of 89.34%, and an overall accuracy of 89%. The model identified 'Moderate' severity X-ray images with high F1-score of 94%, but having lower F1-score for both Mild and Severe classes which might be attributed to class imbalanced in the dataset. The model's classification report for Pneumonia Severity Diagnostic Threshold2 Model is as presented in Table 5.

Figure 4 provides a graphical representation of the Pneumonia Severity Classification Model2 accuracy scores across 10 epochs, and Figure 5 shows Pneumonia Severity Diagnostic Threshold2 Model training loss values, ranging from 0.2 to 0.6.

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TABLE 4
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD2 TRAINING RESULT

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.4245	0.8820	0.3727	0.8825
2	0.3737	0.8923	0.3609	0.8925
3	0.3464	0.8923	0.3691	0.8934
4	0.3278	0.8916	0.3492	0.8925
5	0.2942	0.8923	0.3431	0.8848
6	0.2778	0.8990	0.3412	0.8813
7	0.2568	0.9023	0.3693	0.8874
8	0.2218	0.9108	0.3772	0.8874
9	0.1876	0.9259	0.3816	0.8624
10	0.1340	0.9513	0.5840	0.8856

TABLE 5
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD1 CLASSIFICATION REPORT

Classes	Precision	Recall	F1-score	Support
0 (Mild)	0.17	0.02	0.03	116
1 (Moderate)	0.89	0.99	0.94	1038
2 (Severe)	0.00	0.00	0.00	9
Accuracy			0.89	1163
Macro avg	0.35	0.34	0.32	1163
Weighted avg	0.81	0.89	0.84	1163

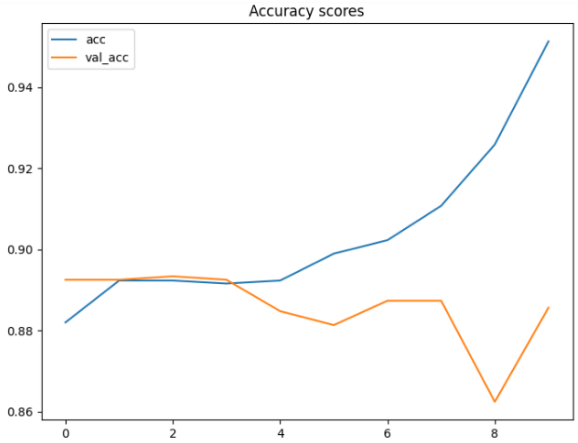

Figure 4. Pneumonia Severity Diagnostic Threshold2 Accuracy score

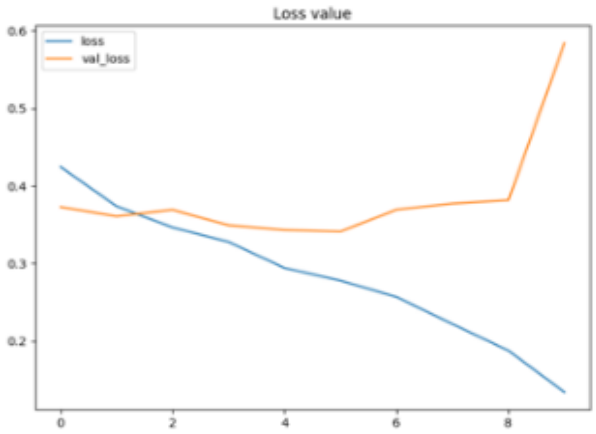

Figure 5. Pneumonia Severity Diagnostic Threshold2 Loss value

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D. Pneumonia Severity Diagnostic Threshold3 Model

The Severity classification of this model was based on Equation (4), developed using the same architecture described above. Table 6 shows the loss and accuracy performance of the training and validation each of the 10 Epochs during the Pneumonia Severity Diagnostic Threshold3 Model training, and Table 7 depicts the model classification report.

TABLE 6
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD3 TRAINING RESULT

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	0.7676	0.5162	0.7319	0.4617
2	0.7234	0.5605	0.6939	0.6432
3	0.6696	0.6530	0.6446	0.6655
4	0.6398	0.6755	0.6442	0.6569
5	0.6193	0.6847	0.6486	0.6793
6	0.6047	0.6947	0.6340	0.6767
7	0.5726	0.7268	0.6549	0.6672
8	0.5271	0.7518	0.6562	0.6741
9	0.4826	0.7869	0.7372	0.6552
10	0.4288	0.8060	0.7043	0.6561

Generally, the overall performance of Pneumonia Severity Diagnostic Threshold3 Model achieved moderate accuracy scores on both the training and validation datasets having highest training accuracy of 72.68%, highest test validation accuracy of 67.93%, and an overall accuracy of 66%. While not excellent, is acceptable, despite the imbalance in the dataset, there is relatively good performance on 'Mild' and 'Moderate' classes, with F1-score of 69% and 62% respectively but very poor performance on 'Severe' class due to few instances representation which might be the case in the hospital settings where the severe cases might be minimal or even absence. The model's classification report for Pneumonia Severity Model3 is presented in Table 7.

TABLE 7
PNEUMONIA SEVERITY DIAGNOSTIC THRESHOLD1 CLASSIFICATION REPORT

Classes	Precision	Recall	F1-score	Support
0 (Mild)	0.68	0.70	0.69	618
1 (Moderate)	0.63	0.62	0.62	536
2 (Severe)	0.00	0.00	0.00	9
Accuracy			0.66	1163
Macro avg	0.44	0.44	0.44	1163
Weighted avg	0.65	0.66	0.65	1163

Figure 6 shows the accuracy score performance of the Pneumonia Severity Diagnostic Threshold3 Model over ten epochs, and Figure 7 shows the model loss value.

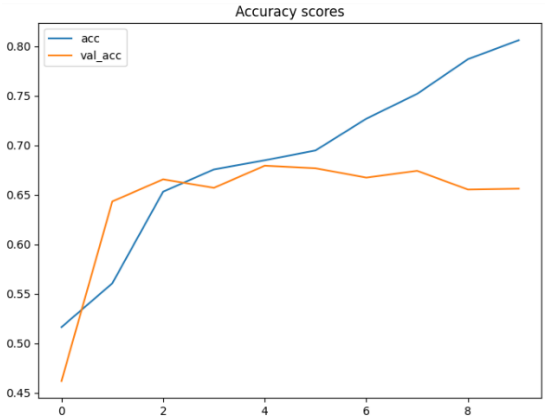

Figure 6. Pneumonia Severity Diagnostic Threshold3 Accuracy score

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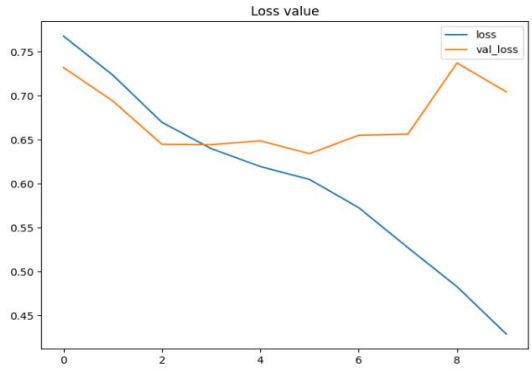

Figure 7. Pneumonia Severity Diagnostic Threshold3 Loss value

E. Classification Evaluation Matrix

Four evaluation metrics: Accuracy, Precision, Recall, F1-score, with four indices, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) were used in determining the performance of the Pneumonia severity threshold models, the metrics are discussed in Olatunde *et al. (*2024)

IV. CONCLUSIONS

All the three Pneumonia Severity Diagnostic Threshold Models performed well in predicting the "Moderate" class, while the Deep Learning Pneumonia Model1 and Model3 can predict both "Mild" and "Moderate" classes, with high accuracy, they do not perform well in predicting "Severe" Class, as a result of minimal representation of the instance in the training data. Model 2 can only predict "Moderate" class. Data balancing through augmentation was not used on the dataset before training to avoid adding unnecessary biases, since the dataset used is a binary labelled (Normal and Pneumonia), hence, the Pneumonia Severity Diagnostic Threshold Models can be used in conjunction with other diagnosis results such as Laboratory and physical examination. Fuzzy logic will be embedded into the architecture to permit inclusion of other diagnosis results such as laboratory test and physical examination in future research.

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