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Intelligent Early Diagnosis System against Strep Throat Infection Using Deep Neural Networks

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Abstract—The most frequent bacterial pathogen causing acute pharyngitis is Group-A hemolytic Streptococcus (GAS), and sore throat is the second most frequent acute infection. The immunological reaction to group A Streptococcus-induced pharyngitis results in Acute Rheumatic Fever (ARF). A genetically vulnerable host for ARF is a streptococcal infection. ARF, which can affect various organs and cause irreparable valve damage and heart failure, is the antecedent to Rheumatic Heart Disease (RHD). RHD, in many countries is Cardiovascular Disease (CVD) refers to a range of conditions that affect the heart and blood vessels, including coronary artery disease, heart attack, heart failure, and stroke. It is important to note that while this approach has demonstrated promising results, further studies and validation are necessary to establish its clinical feasibility and reliability. Further research can also be done to evaluate the generalization of the model to larger and diverse patient populations. The results showed that using Image Synthesis-based augmentation improved the ROC-AUC scores compared to basic data augmentation. The proposed method could be a valuable tool for healthcare professionals to quickly and accurately diagnose strep throat, leading to timely treatment and improved patient outcomes. The experimental findings indicate that the suggested detection approach for strep throat has a high level of accuracy and effectiveness. The approach has an average sensitivity of 93.1%, average specificity of 96.7%, and an overall accuracy of 96.3%. The ROC-AUC of 0.989 suggests that the approach is effective at distinguishing between positive and negative cases of strep throat. These results indicate that the suggested detection approach is a promising tool for accurately identifying cases of strep throat.

Keywords- Augmentation; Class Activation Mapping; Deep Neural Network; Heart Disease; Rheumatic Heart Disease; Semantic Segmentation;

I. INTRODUCTION

An auto-immune inflammatory reaction to infection with streptococcal bacteria causes rheumatic fever, which occurs whenever the immune system reacts against the body tissues it includes the inflaming and scarring of the heart valves, causes RHD which is a life-threatening heart condition that results in the damaging of the heart condition. This is very common in childhood. Early detection, evaluation, and treatment have made the prevention and control of RHD feasible. Furthermore, a false strep throat diagnosis could result in ineffective antibiotic administration, which would breed bacterial resistance.

This paper focuses on developing a Deep Learning (DL) based method to accurately diagnose RHD in individuals. RHD has significant impacts on global health, causing both illness and death, especially in developing countries. The Global Burden of Disease report (GBD 2020), estimates that RHD affects at least 33 million people and results in 30,000 deaths each year, with children, adolescents, and pregnant women being particularly vulnerable [1]. The proposed DL method is designed to enhance the accuracy of RHD diagnosis with the aim of facilitating early interventions and reducing the adverse effects of the disease.

Figure 1 provides a visual representation of the progression of RHD, starting with an infected throat and leading to heart valve damage. The primary cause of the mortality and morbidity that occur with RHD is damage to the cardiac valves brought on by an inflammatory response to GAS infection (typically, childhood sore throat). The only cardiovascular condition with widespread impact that has been proved to be entirely avoidable is RHD [2].

Most sore throats are caused by viruses or bacteria. The Group-A streptococcal Bacteria is the primary cause of streptococcal infection which mainly affects the throat and the tonsils. These bacteria are very contagious and spread from one person to another either through direct contact or through nasal droplets like talking, sneezing and coughing. The various symptoms of the GAS infection include whooping cough, change in voice, Runny nose and pink eyes (Conjunctivitis).

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ARF is a serious complication that can occur as a result of untreated RHD. If the infection persists for about 3 to 6 weeks, it can trigger an immune response that causes inflammation in different parts of the body, including the joints, heart, and skin. ARF can result in serious long-term complications, including heart damage and joint damage, which can lead to long-term

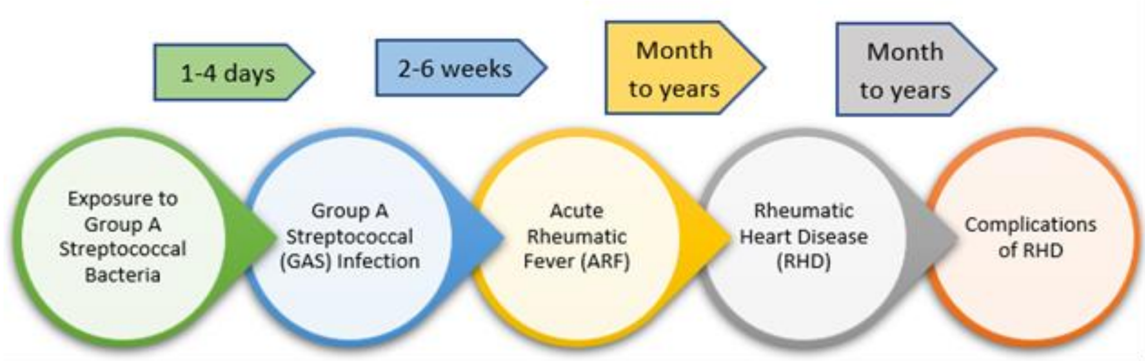

Figure 1. Progression of RHD

disability and even death. For this reason, it is crucial to diagnose and treat RHD promptly to prevent the development of ARF and other serious complications [3].

This Acute Rheumatic Fever is an inflammatory disease which is mainly caused when the strep throat infection is not treated properly. This fever results in damage to the heart valves or even heart failure, but when treated at the early stage damage to the heart valves is caused due to inflammation and also helps in the prevention of the fever prevailing again. Rheumatic fever if not treated properly at the early stage can lead to rheumatic heart disease which leads to permanent damage to the heart valves. At times major surjery is required for the replacement of the damaged valves, depending upon the severity of the disease.

Despite the progress made in reducing the burden of RHD, it remains a significant public health problem in many developing countries. The World Health Organization (WHO) and partners have developed a comprehensive strategy for the prevention and control of RHD, including increasing access to RHD screening and treatment, strengthening health systems, and improving disease surveillance. Public health interventions can be very important in reducing the spread of diseases by promoting healthy behaviors and providing access to necessary resources. Education and awareness campaigns can help individuals understand the importance of hygiene and how to practice it effectively. In addition, providing access to preventative care and early treatment can help control the spread of diseases and reduce their impact on public health. Furthermore, early detection and prompt treatment of streptococcal infections is critical to prevent the development of RHD, and continued investment in research and development of vaccines and other preventive measures is needed to address this ongoing public health challenge.

Clinical samples are subjected to mass spectrometry utilizing the SWATH-MS method, which employs a Data-Independent Acquisition (DIA) strategy for precise protein identification and quantification.

The most popular way of diagnosis is a clinical judgement based on the Centor score which otherwise called the strep throat criteria, which is determined by a set of parameters including coughing, fever greater than 38℃, Swelling in the tonsils and tender or swollen cervical lymph nodes. Another clinical way for diagnosing streptococcal pharyngitis is throat culture, which involves adding a sample of throat cells to a material that will encourage the growth of the bacteria and will diagnose the condition. Touch spray ionization mass spectrometry is also used to diagnose strep throat. Therefore, providing all patients with a prompt and accessible diagnosis remains difficult. But skilled medical professionals or specialists are required for these diagnostic techniques. But, these manual approaches for strep throat classification require highly qualified personnel, pricey reagents, and expensive equipment. Also, mistakes could occur as a result of poor decisions [10]. In order to solve this issue, an exact and automated system is now required.

A new explosion of Machine Learning (ML) expertise, the identification and detection of throat infections from images could be greatly improved, reducing humans time, cost, and effort. With the aid of various ML technologies, numerous researchers have already achieved amazing success in numerous multi-dimensional data analysis tasks like image processing, pattern detection in images, and picture categorization. In order to categorize and identify Strep throat infection from throat images, the researcher has suggested a number of automated systems. Among these, deep Convolutional Neural Network (CNN) remarkable things about DL models is their potential for making an impact on various industries and fields. Amazing accuracy has been found in the classification of microscopic cell images, diabetic retinopathy, and other things.

As a result, the process is difficult, and the creation of an algorithm for strep throat infections would improve access to clinical settings in rural areas as well. Classifying Tumour images, identifying retinal diseases, and identifying lung nodules have all been accomplished using DL architecture like Xception. As a result, the converted Xception DL model to classify and detect strep throat infection.

An automated approach leveraging the geometric characteristics of tuberculosis cells to categories tuberculosis germs using neural networks [5]. By using convolutional networks on the ImageNet dataset [6] created AlexNet CNN architecture revolutionized image classification. Yes, the dataset dimensions are increased by a factor of 2^11, or 2048, through augmentation. This significant increase of the dataset allows for better training of the DL models and ultimately leads to improved performance in terms of accuracy and other evaluation metrics. Augmentation helps in reducing overfitting, increasing generalization, and improving the robustness of the models. By synthesizing new data from the original dataset, augmentation can also lead to a more diverse training set, making the models more resistant to variations in the data distribution. In order to achieve this, 224 * 224 patches of the original photos are randomly selected, they are horizontally flipped, and PCA colour augmentation is used to modify the RGB channel intensity.

The proposed method influences the DL algorithms and image augmentation techniques to classify throat images as healthy or infected with streptococcal pharyngitis. The collected throat images were transformed using augmentation and color modification algorithms, and then fed into DL models. The investigational outcomes exhibited the projected process accomplished top sensitivity, specificity, and accuracy in detecting strep throats, with an accuracy rate of 96.3% and ROC-AUC of 0.989. For the proposed system, the images of the throat that was collected its transformed using augmentation and colour modification algorithms. Then DL techniques are used to identify between healthy and streptococcal pharyngitis (or strep) throats. This assessed the effectiveness of various CNN model variations followed by various classifiers for multi-level classification between strep and healthy throats.

Here is a description of how this work is organized: A description of the relevant research carried out in the same field is provided in Section 2. All the information pertinent to the dataset and description of proposed CNN model is described in Section 3 of the paper. In Section 4, the result and discussion for the experiments performed on several pre-trained CNN model versions as well as the findings of using various classifiers were given.

II. Related Work

The use of ML methods for thoracic disorder detection has gained attention in recent years, particularly in the medical field [7]. DL, in particular, has proven to be a powerful tool in medical imaging applications since its rise to prominence in 2012.

Data augmentation with GANs has been shown to enhance classification performance. The highlights the potential of using GAN-based image synthesis as a data augmentation technique in medical image analysis, particularly in improving the performance of DL models for classifying liver lesions [8]. It emphasizes the importance of using advanced techniques to enhance the accuracy of medical diagnoses, which can ultimately lead to better patient outcomes (from 78.6% to 92.4%) and specificity (from 88.4% to 85.7%).

Data augmentation performances, such as geometric, photometric conversions, also remained investigated for their effectiveness in improving classification performance. The results compared of various techniques such as flipping, rotations, cropping, and color space modifications using the Caltech101 dataset [9]. In addition to data augmentation, regularization techniques like PatchShuffle Regularization have been proposed to progress the classification recital by using PatchShuffle Regularization, a particular kernel filter that flips pixel values randomly achieved a CIFAR-10 error rate of 5.66% as opposed to 6.33% without it.

An approach to identify pulmonary tuberculosis was set - up by modelling it after the architecture of two separate DCNNs, AlexNet and GoogleNet [10]. In 2017, the use of DL techniques, specifically Mask-RCNN algorithm, in medical image analysis has shown promising results and is increasingly being used in various medical fields. The ability of the algorithm to effectively extract information on multiple scales and its success in instance segmentation make it a valuable tool in the detection and classification of various medical conditions [11]. The use of Data Augmentation and GAN-based image synthesis also shows a critical part in improving the recital of these algorithms in medical image classification tasks. The study of the Mask-RCNN algorithm in segmenting the posterior pharyngeal wall image provides a new direction for enhancing the sampling effectiveness of the throat swab robot [12].

Image recognition model advancements have a wide range of applications in computer vision tasks, including Object Detection and Semantic Segmentation. Object Detection involves detecting and positioning objects in an image, while Semantic Segmentation involves assigning a label or class to each pixel in an image, thereby providing a dense and per-pixel labeling of the scene. These computer vision tasks have practical applications in various domains such as medical imaging, autonomous vehicles, and security systems, among others. By leveraging the advances in image recognition models, these tasks can be performed more accurately, efficiently, and with greater ease.

Studies have shown that some diseases, such as diabetic internal organ diseases, and heart and kidney ailments, can be

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detected using colour intensity measurements. The limitations in these methods include difficulty in obtaining consistent and accurate colour intensity values due to differences in lighting and camera settings, as well as the subjectivity in interpreting tongue colour changes. Additionally, the tongue colour intensity-based methods may not be able to provide comprehensive information about the underlying medical condition and may need to be combined with other medical diagnostic techniques for a more accurate diagnosis. Nevertheless, the integration of computer vision procedures and ML processes has the potential to revolutionize the medical field by providing efficient and non-invasive ways of diagnosing diseases based on visual information.

Deep Neural Networks (DNN) can be used to diagnose heart disease, which is a critical area in neural networks. Talos Hyper-parameter optimization is used on the Heart Disease UCI data set to show that it is more efficient than other. In comparison to further processes and optimization, it has demonstrated virtuous prediction outcomes [13]. In this paper, the Talos optimization to deploy DNN is used. Talos is a hyper parameter optimization framework for Keras, which automates the process of hyper parameter tuning. Talos is known to outperform other hyper parameter optimization techniques in some cases in terms of accuracy, but it is important to note that the choice of hyper parameters can significantly impact the performance of a DL model. Using Talos optimization to create and deploy a Keras model on heart disease dataset is a promising use case, as it can potentially improve the accuracy of predictions and contribute to better health outcomes.

Deep neural networks, particularly CNNs, are being increasingly used in medical image classification tasks because of their ability to learn high-level representations from large amounts of data. These networks are capable of learning complex relationships between input images and target labels and have demonstrated state-of-the-art performance in many medical image classification tasks. For example, they have been successfully used for disease diagnosis based on tongue color features and disease subtype classification based on texture features [14]. The use of DNN in medical image classification tasks could potentially have a significant impact on improving medical diagnosis and treatment outcomes. RELU function, data augmentation, and dropout are important concepts that have been used in the development of CNNs. The number of research articles published on the design and applications of CNNs in medical image analysis has enlarged suggestively now a days, reflecting the growing popularity of this architecture for such tasks [15].

Visualization techniques, such as the Improved Class Activation Mapping (ICAM) [9], can help users better understand the predictions made by CNNs and improve their trust in the accuracy of the automatic classification. However, further quantitative analysis may be necessary to validate the localization results obtained from these techniques.

III. PROPOSED SYSTEM

A. Methods

1) Data Collection:

In this section, the image dataset that was gathered and shows several image augmentations for expanding the number of samples to detect the throat infection, perhaps enabling an initial diagnosis based on images are provided. Image data augmentation is a method that turns existing images into new ones. In order to identify significant image sub-regions and extract the mastered texture patterns, class activation mapping was proposed. Finally, this dataset to train CNN models for automatic image classification were used.

The Internet-based self-taken throat images used in this investigation were made available to the public. A dataset made up of 208 normal throat images and 131 images of the throat with pharyngitis was gathered from the Mendeley Data repository. In order to clarify the image domains, ambiguous images were removed and images having the features of either a Strep Throat or a healthy throat were manually categorized. In conclusion, our initial dataset was assembled with two categories, comprising 208 images of healthy throats and 131 images of throats affected by strep.

To apply DL to a new dataset, the data was randomly divided into three sets: training (50%), testing (25%), and validation (25%). Table 2 contains a detailed breakdown of the data distribution and augmentation. The input used in the models consisted solely of images of the tonsils and throat without any modification to reduce intra-class variance. The images were resized to a resolution of 256x256x3 pixels in PNG format to enable the use of DL models.

This study utilized open and de-identified data obtained from the web, and thus, approval from an ethics committee was not required. All datasets used in the development of the DL model can be accessed in the Mendeley Data repositories.

2) Data Collection:

In order to accurately and effectively extract features from throat images, the preprocessing phase is required. Data Augmentation and Class activation mapping are the main parts of preprocessing steps for the proposed model.

3) *Data Augmentation:*

Data augmentation is essential for DL training due to the lack of datasets and their unbalanced distribution. To train DL models, simple data augmentation methods including flipping, translating, rotating, and changing the intensity of the data have been used. Earlier trainings tried to train DL representations with synthetic images to improve classification accuracy. The image

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reshaping, horizontal flipping, and rotating based data augmentation techniques to improve diagnosis accuracy were used.

a) Image Reshaping:

A common image processing principle that serves a variety of functions is interpolation. Interpolation is a common component of various kinds of image modifications. Similar to this, interpolating the pixel values from the original image is required when scaling an image. There are many difficulties with interpolation, including aliasing, blurring, edge halo, and computing speed.

In a similar fashion, for redundant and noisy approaches, the actual image may be positioned all throughout the square container. For each phase, the randomized algorithms place the reshaping window in a different random position. By using linear interpolation over a neighborhood of 4 by 4, the pixel value is calculated. A constant value, such as 0 or 255, or random or Gaussian noise can be used to fill the empty area while the actual image is translated in a certain track. An edge length equivalent to the source image's shorter side would be used for the output square image. Such images contain information that is a subset of the original image.

b) Horizontal Flipping

The decision of whether to flip an image horizontally or vertically depends on the subject of the photograph. Flipping an image can increase the number of images in a collection without resorting to artificial processing. In order to view the left and right sides of an image, it must be horizontally rotated. The fx and fy components in Equation 1 are calculated based on the pixel's current location after reflection along the horizontal y-axis.

$$\begin{bmatrix} fx \\ fy \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (1)$$

Equation 2 describes the new coordinates of each pixel after reflecting along the horizontal axis, where the fx coordinate represents the pixel's new horizontal position and the fy coordinate represents the pixel's original vertical position.

$$\begin{bmatrix} \boldsymbol{fx} \\ \boldsymbol{fy} \end{bmatrix} = \begin{bmatrix} \mathbf{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{y} \end{bmatrix} \qquad (2)$$

c) Rotating

Rotating an image around an axis at angles between 1° and 359°, either clockwise or counterclockwise, is a common technique for improving geometric image data. Figure 2 and 3 demonstrate how images can be rotated by a specific angle in an additive manner. The safety of using rotation augmentations depends heavily on the degree of rotation parameter. On digit identification tests, slight rotations, such as those between 1° and 20° or -1° to -20°, may be helpful, but as the degree of rotation grows after transformation, the data's label is no longer preserved.

$$\begin{bmatrix} \boldsymbol{fx} \\ \boldsymbol{fy} \end{bmatrix} = \begin{bmatrix} \boldsymbol{cos\theta} & \boldsymbol{-sin\theta} \\ \boldsymbol{sin\theta} & \boldsymbol{cos\theta} \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{y} \end{bmatrix} \qquad (3)$$

The raw image is represented by the x and y duos of synchronizes, whereas the new positions of each pixel after rotation are represented by fx and fy, as indicated in Equation 3.

4) *Class Activation Mapping:*

Class Activation Mapping (CAM) is a technique for visualizing the textural regions that are distinguishing for the classification of illness subtypes. By analyzing and grouping the highlighted sub-image regions, able to confirm the assumption that similar illness subtypes have specific visual patterns.

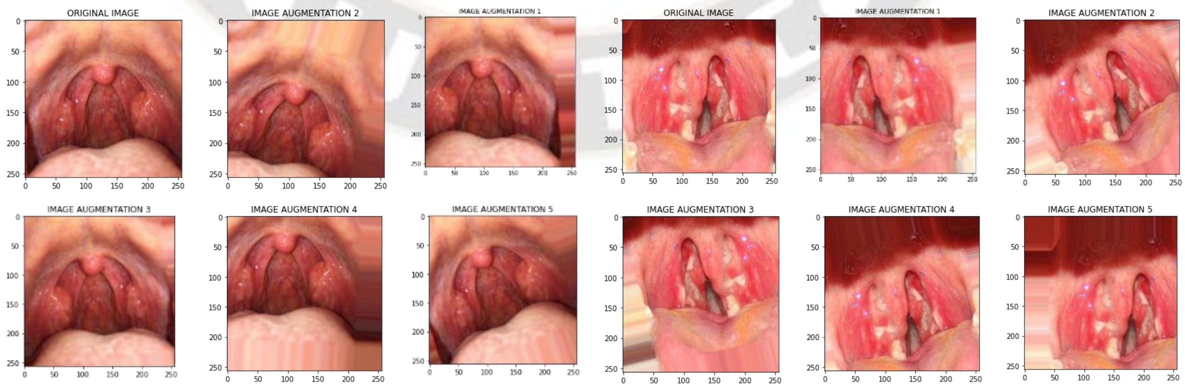

Figure 2. Data augmentation using Rotation of Non-Infected Images and Infected Images

In addition to giving users an effective means to comprehend CNN's predictions, the proposed CAM also aids in persuading users that the automatic categorization method is accurate. The discriminative picture regions that the CNN used to identify a given category are displayed in a class activation map for that category.

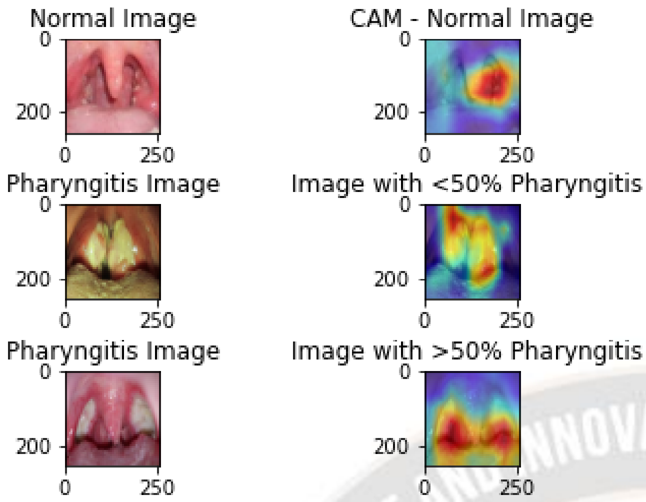

Figure 3. Class Activation Mapping for Healthy Image and Infected Image

Figure 3 shows the generated healthy and strep throat images using CAM. Strep throat is a bacterial infection that can cause several symptoms, such as the presence of white and yellow spots on the tonsils and the back of the mouth, as well as red patches on the roof of the mouth. In addition, the tonsils may appear swollen and red. These symptoms can help distinguish strep throat from other conditions that cause a sore throat. It is important to seek medical attention if you suspect that you or someone you know may have strep throat, as prompt treatment with antibiotics can help prevent complications and reduce the risk of transmission to others. These signs of bacterial inflammation are represented by these symptoms. Therefore, to identify strep throat symptoms, our suggested technique extracts these properties. Our method was developed and put into use only to identify between strep throats and healthy ones.

5) *Development of CNN model in DL*

There are numerous algorithms for DL, each of which has benefits and drawbacks. DL has become a popular research area. Nearly all of our image processing is covered by these algorithms, which primarily concentrate on classification and segmentation. DL is on the rise and is a current hot topic now for image classification. The most common structure among them is CNN.

Many different tasks, including image classification, localization, detection, segmentation, and registration, have been carried out using CNNs. Due to its distinctive ability to maintain local image associations while conducting dimensionality reduction, CNNs are the most widely ML method in image identification and visual learning tasks.

In order to enhance the data, common DL models were trained. The study's limited image dataset makes it challenging and time-consuming to design a unique DL method. Data augmentation is a useful strategy for training DL models that utilize pre-trained architectures and have limited datasets. The technique involves applying various transformations to the original data, such as scaling, flipping, and rotating images, to generate new and diverse images for the model to learn from. This approach can improve the generalization of the model and prevent overfitting. By utilizing pre-trained architectures and data augmentation, DL models can achieve better performance, even with small datasets. Moreover, pre-trained learning models were used in this work to classify images of the throat.

Table 1 describes the different layers present in the proposed CNN model when compared to the basic CNN model architecture. Here two layers of encoders convolution layers are being used. The Convolution layer being the first layer of the convolution neural network is the core block of CNN in which most of the computations are being performed. Here the components such as the input data, filter and feature map are required, which include the height, width and depth of the input data. The feature detector also called the kernel or the filter is used to move across the receptive field of the image.

In the basic CNN model, the concatenation feature is being imported which is mainly used for increasing the precision of learning and discovering the new architecture whereas in the proposed methodology batch normalization is being used by the ender and decoder. In this from mean of the hidden activation layer has to be calculated from our batch input from layer h is shown in Equation 4.

$$\boldsymbol{\mu} = \frac{1}{m} \Sigma \boldsymbol{h}_i \tag{4}$$

Where m is the number of neurons at the $\boldsymbol{h^{th}}$layer. Then the standard deviation of the hidden activations is referred in Equation 5.

Table 1. Architecture Layers of Basic CNN Model vs Proposed CNN Model

S No	Basic Architecture	InceptionResNetV2 Architecture
1	Encoder 8's Convolution Layer	Encoder 8's Convolution Layer
2	Encoder 8's Convolution Layer	Encoder 8's Convolution Layer
3	importing the concatenation feature	Batch normalisation is used by the encoder and decoder
4	Channels controlled by the bottleneck layer	Channels controlled by the bottleneck layer

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5	Two convolution layers are present in the encoder and decoder blocks.	The feature re-use policy is applied by Semantic Gap.

$$\sigma = \left[\frac{1}{m}\,\Sigma(h_i - \mu)^2\right]^{1/2} \qquad (5)$$

followed by the normalization of the hidden layer is shown in Equation 6.

$$h_{i(norm)} = \frac{(h_i - \mu)}{\sigma - \varepsilon} \qquad (6)$$

where ε is the smoothening term. The term batch normalization in encoder and decoder is speed up the training process by normalizing the hidden layer, to solve the problem of internal covariate shift and smoothen the loss function by optimizing the model parameters which intern speeds up the training of the model. The channels are controlled by the bottleneck layer, which is a layer with fewer neurons than the layer below or above it. The main reason for having this layer is because it helps the network to compress the salient feature of the target variables to fit correctly into the available space.

To construct multi-level classifiers, Xception, InceptionResNetV2, and Convolutional Networks were utilized. While the training set was used to train the models, the validation data was used to evaluate how well they had been trained. The trained networks' weights were modified after the pre-trained CNN models were downloaded from the ImageNet database. To implement this approach, the high-level features are precisely adjusted while preserving the weights of a few lower layers to prevent overfitting. In the DL models, each input image was resized to a 256*256*3-pixel resolution. By establishing a threshold value to categorize data, our study's resolution was suitable for pharyngitis recognition utilizing a multilevel approach. For each CNN model, the ADAM optimizer with a cross-entropy loss and 0.0001 learning rate was also applied. The proposed DL model for strep throat infection diagnosis with multi-level categorization is shown in Figure 5.

The optimizer is a crucial element in the training of neural networks that updates model parameters to minimize the loss function, which represents the difference between predicted and actual outputs. The optimizer changes the network setup during training to reduce the loss function and improve the accuracy of the model's predictions. Optimizers use different techniques such as stochastic gradient descent and its variants to adjust the network parameters and minimize the loss function. In our research, it enhanced a CNN model's completely linked layer. For instance, only the final fully connected layer of ResNet50 was trained using the training dataset, but the preceding 49 levels of ResNet50 were left unchanged. The final classifier model was chosen based on the validation dataset's greatest accuracy. The pre-trained InceptionResNetV2 model's final layer's feature vectors were retrieved in order to train the test instance.

Algorithm: Procedure of Proposed CNN Model
Input: Image Dataset
Output: Classified outputs

Begin
1: Get health data inputs as an image, $\boldsymbol{f(i)}$
2: Call $\boldsymbol{h(i)}$for reshaping
add a constant value, such as 0 or 255, or random or Gaussian noise
3: Find $\boldsymbol{m(f)}$for flipping by fx, fy
4: Call Rotate $\boldsymbol{r(f)}$, for all fx, fy coordinates between 1° and 20° or -1° to -20° in left and right
5: Activate CAM function to generate healthy and strep throat image
6: Call $\boldsymbol{\mu, h(i)}$function to activate the hidden layer of CNN model
7: Initiate mean, standard deviation function for generated final data, $\boldsymbol{e(i)}$
8: Forward the generated image in to input layer functions of CNN
9: Repeat for all data streams recursively.
10: Returns the prediction result with optimal features

The above actions describe the technical features of proposed CNN approach over throat image data. The data observed and prepressed with different functions along with CNN function. The CNN model optimizer finds the functional scores from the output layer to classify the multilevel strep throat infection with the help of threshold value.

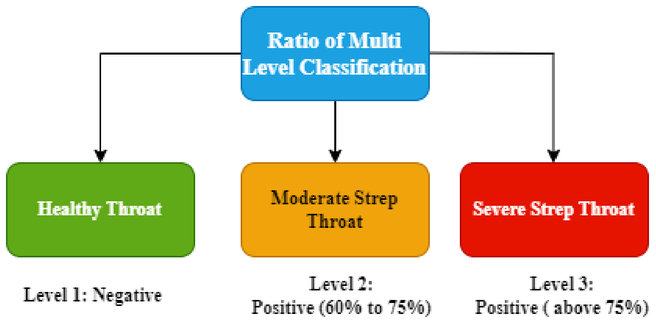

Figure 4: Ratio of Multi-Level Classification for Strep Throat Infection

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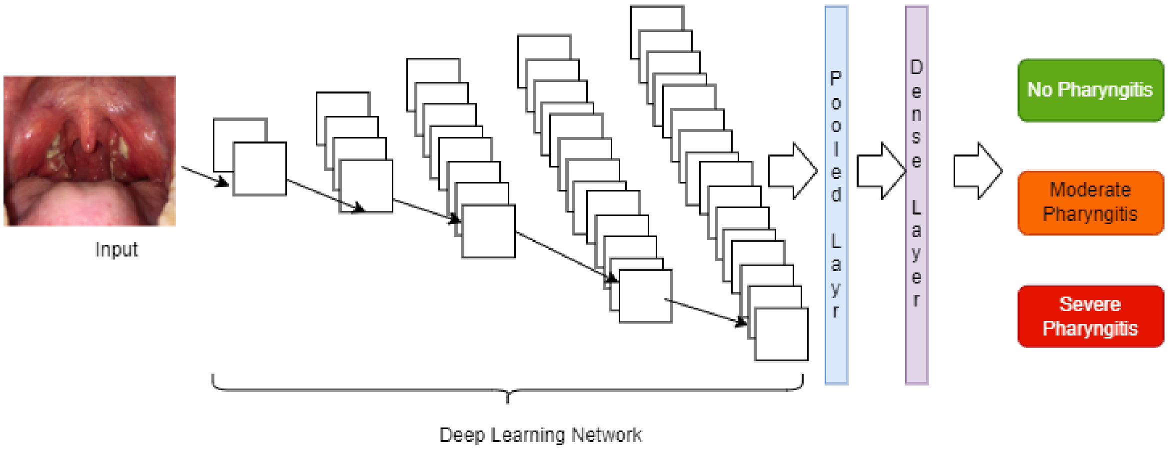

Figure 5. Proposed DL Model for Strep Throat (Pharyngitis) Diagnosis

In this research, it classifies the disease into 3 levels of classification such as healthy throat, moderate level of strep throat infection and severe strep throat infection. The threshold value for the multi-level identification of Strep Throat Infection based on the average of finding were set initially. The cut off value of classification is the ratio of binary classification. As the binary value of 0 taken as no pharyngitis and another binary value 1 had been taken the average result of accuracy between 60% to 75% as Strep Throat with moderate level and more than 75% consider as severe Strep Throat Infection as exposed in Figure 4.

IV. Experiments and Results

To address complex problem of pharyngitis identification, a DL model employing augmentation is being created. After training the dataset, healthy throat images are converted into pathologic images, whereas pharyngitis-related images could be converted into healthy ones. Finally, a balanced augmented training dataset is created with 1500 images of pharyngitis and 1500 photographs of normal skin. The resulting expanded dataset is used to train the CNN models using the transfer learning method. The following measures were used to gauge how well the CNN models performed,

- Accuracy
- Sensitivity
- Specificity
- Precision
- Area Under the Curve (AUC)

Accuracy: The performance of the model across all classes is often described by the metric of accuracy is shown in Equation 7. The ratio of the number of accurate predictions to all predictions is used to compute it.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+TN+FP+FN}} \qquad (7)$$

Sensitivity: The sensitivity (recall) is determined as the proportion of Positive samples that were correctly identified as Positive to all Positive samples as mentioned in Equation 8.

$$\boldsymbol{Sensitivity} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \qquad (8)$$

Specificity: Specificity measures how many true negatives the model accurately predicts. It is often referred to as the true negative rate is described in Equation 9.

$$\boldsymbol{Sepecificity} = \frac{\boldsymbol{TN}}{\boldsymbol{TN+FP}} \qquad (9)$$

Precision: Precision is a measure of the accuracy of a classifier when it predicts the positive class. It is calculated as the ratio of true positive predictions to the sum of true positive and false positive predictions is given in Equation 10. In other words, precision represents the proportion of correctly identified positive instances out of all instances that the model has labeled as positive. High precision means that the classifier has a low false positive rate and correctly identifies a high proportion of positive instances.

$$\boldsymbol{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \qquad (10)$$

For the training dataset, 900 pictures of a normal healthy throat and 500 pictures of pharyngitis are randomly chosen, and for the test dataset, 500 images of a normal throat and 300 images of pharyngitis are chosen. The Image Synthesis Augmentation models were trained using straightforward augmentation techniques to transform normal throat images to pharyngitis images, and vice versa. It is common practice in DL to use a large dataset to train a classifier, as this helps the model learn to generalize to new, unseen data. The researchers were able to expand the training dataset in this situation by using picture synthesis-based augmentation, which might enhance the performance of the diagnostic classifier model.

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In Table 2, by using image synthesis to generate additional training examples, the model is exposed to a larger variety of variations and variations in the data, which can help it learn to distinguish between normal throat images and pharyngitis images more effectively. This can ultimately lead to a more accurate diagnostic classifier that can better diagnose pharyngitis based on throat images.

It is important to note that while increasing the size of the training set can be beneficial, it is not the only factor that determines the performance of a classifier. Other elements including model design, optimization strategies, and regularization approaches can also significantly affect the classifier's performance.

Table 2. Training and Testing Dataset

Models	Class	Number of Training Set	Number of Testing Set
Raw data	Normal Throat Images	104	52
	Strep Throat Images	65	33
Basic Augmentation	Normal Throat Images	900	500
	Strep Throat Images	500	300
Proposed Image Synthesis Augmentation	Normal Throat Images	1500	700
	Strep Throat Images	1500	600

Using the final augmented sample as training data, the transfer learning method is used to train the CNN models. The final Image Synthesis-based augmentation model for the strep throat image took 10 hours of training time over 20 epochs. The Image Synthesis-based Augmentation By introducing white or grey patches, the model improved the original photos' depictions of the tonsils and throat wall's redness.

It can be seen from Figure 6 that the accuracy of the training set increases with the number of iterations, while the accuracy of the testing set increases initially but then plateaus. This is indicative of overfitting, where the model becomes too specialized to the training data and is unable to generalize well to new data. In order to address overfitting, various techniques such as regularization, early stopping, or using a smaller network architecture can be employed.

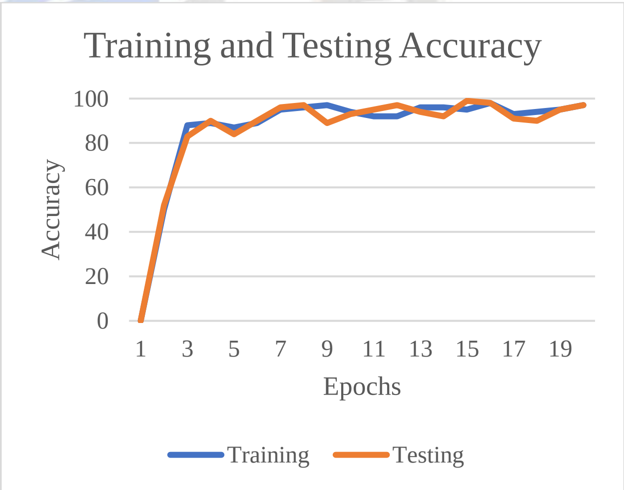

Figure 6. Accuracy Learning Curves for Proposed Model

Figure 7 displays the training and testing sets' loss learning curves with regard to accuracy and iterations. The loss is a measure of how well the model is performing. In this case, the loss is decreasing for both the training and testing sets, which is a good sign as it indicates that the model is learning and improving. However, if the gap between the training and testing loss increases, it may indicate overfitting as well.

In conclusion, the results shown in Figure 6 and 7 suggest that the InceptionResNetV2 CNN model has the potential to be a useful tool for the diagnosis of pharyngitis based on throat images. However, further validation on a larger and diverse

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dataset, as well as further experimentation with different network architectures and data augmentation techniques, would be necessary to determine the optimal configuration for this task.

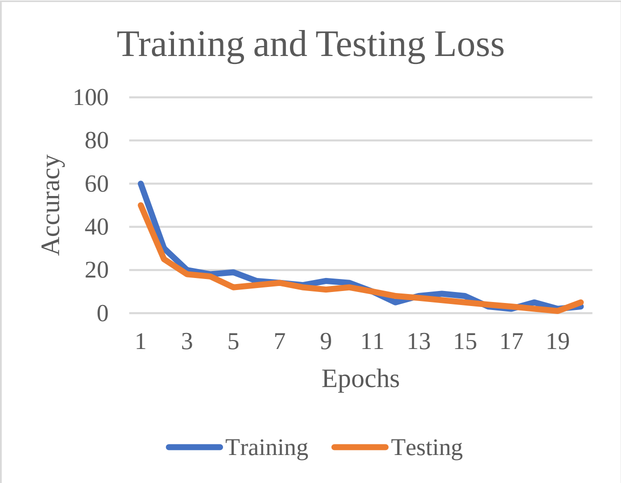

Figure 7. Loss Learning Curves for Proposed Model

The results of using InceptionResNetV2 and Xception with basic data augmentation were 0.968 and 0.956 ROC-AUC, respectively. However, the use of Image Synthesis-based Augmentation led to improved results, with an ROC-AUC of 0.989. Both models accurately diagnosed Strep Throat Infection, with InceptionResNetV2 having a 96.3% accuracy, 92.90% sensitivity, and 96.9% specificity, and Xception having a 95.2% accuracy, 93.1% sensitivity, and 96.7% specificity as shown in Table 3. The models that utilized Image Synthesis-based Augmentation performed better than those with basic augmentation, as evidenced by the better PRC-AUC results [8-9].

The threshold value for the multi-level identification of Strep Throat Infection based on the average of findings is set. The cut-off value of classification is the ratio of binary classification. As the binary value of 0 was taken as no pharyngitis and another binary value of 1 had been taken the average result of accuracy was between 60% to 75% as pharyngitis with moderate level and more than 75% consider as severe pharyngitis.

Table 3. Classification Performance for Strep Throat Detection

Model		AUC	Accuracy %	Sensitivity %	Specificity %	Precision %
Basic augmentation	InceptionResNetV2	0.968	92.9	89.7	94.5	0.877
	Xception	0.956	92.1	88.9	93.9	0.875
Proposed Image Synthesis Augmentation	InceptionResNetV2	0.994	96.3	92.9	96.9	0.986
	Xception	0.989	95.2	93.1	96.7	0.977

In this study, GANs utilized to create synthetic images of the neck for the purpose of improving diagnostic accuracy. The final DL model was able to achieve remarkable results in diagnosing pharyngitis using throat images. This could be of great benefit to individuals who require screening for severe pharyngitis and are experiencing painful throats. However, a limitation of the study was the limited ability of DL models to generalize decision boundaries from a small dataset. To overcome this challenge, it employed a transfer learning approach using pre-trained CNNs, a strategy commonly used in few-shot learning.

V. Conclusion

In this research, the proposed DL model for severe Strep Throat Infection detection is based on transfer learning. The recommended detection method detects strep throats with a 96.3% accuracy rate and ROC-AUC of 0.989, and has average sensitivity, specificity, and accuracy values of 93.1%, 96.7%, and 96.7%, respectively. The objective of this work was to create a DL-based method for precisely and quickly identifying cases of pharyngitis. This could enable prompt and efficient treatment, mitigating any potential negative effects. The method uses a grouping of data augmentation and transfer learning, relying on pre-trained CNNs, similar to other few-shot learning techniques. The results showed that the use of synthetic images generated by GANs improved the diagnostic precision, leading to an accuracy of over 95% for both the InceptionResNetV2 and Xception models. However, the limited size of the dataset still poses a challenge for the generalization of the models' decision boundaries.

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